Forecasting Demand for Weapon System Items

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The Defense Logistics Agency (DLA), the DoD's wholesale manager for consumable hardware items, can improve forecasts of demand for weapon system items by changing its forecasting method to single exponential smoothing of historical demand.

Overall, this method outperforms DLA's current forecasting method, as well as a program-based forecast, when forecasts are ranked in terms of supply performance for a given level of inventory investment. The program-based forecast performed slightly better than single exponential smoothing on single-application items from weapon systems with decreasing programs, but we do not recommend program-based forecasts even in this case, because of the difficulty of implementation. In contrast, single exponential smoothing is straightforward to implement, and it is already an option under DLA's Composite Forecasting, now under development.

DLA should continue its current effort to project the effect of weapon system phaseouts on item demand. Item managers' knowledge could then be used to reduce stock levels and buys for affected items.

14. SUBJECT TERMS
DLA, Defense Logistics Agency, demand, demand forecast, density, EOQ, Economic Order Quantity, exponential smoothing, flying hours, forecast, inventory, inventory management, inventory model, nonoverhaul demand, overhauls, overhaul demand, program, program-based forecast, simulation, smoothing constant, weapon system items, wholesale response time, wholesale supply

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Forecasting Demand for Weapon System Items

Executive Summary

High-level management at the Defense Logistics Agency (DLA) has been concerned for some time that DLA's current, historical-demand-based forecast for consumable weapon system items will tend to overestimate demand in an era of shrinking force structure. Excessive demand estimates, of course, lead to unnecessary acquisition and excess stock.

We examined whether the forecasting of demand for weapon system items could be improved by using program data such as weapon system densities (the number of units of a weapon system), flying hours, steaming hours, rounds fired, or planned overhauls. Program-based forecasting has the obvious, intuitive appeal of responsiveness to the planned program, but its effect on inventory performance – say in terms of average wholesale response time for a given level of inventory investment – is far less apparent. We found that program-based forecasting showed little, if any, improvement over demand-based forecasting.

We analyzed relationships between (1) demand histories for stocked, demand-based consumable weapon system items and (2) weapon system densities over a nine-year period. For aviation systems, we examined the relationships between flying hours and nonoverhaul demand, as well as those between programmed overhauls and overhaul demand. In all cases, we focused on single-application items, where the effect of program on demand, if present, would be most pronounced. We found

- only weak-to-moderate correlation between demand and program for most of the weapon systems in our sample, and
- demand volatility of much larger magnitude than the program-driven trend, where one is present, over periods comparable to the procurement lead-times of DLA items.

Using an inventory simulator that we developed, we measured the average wholesale response time at various levels of inventory investment for the current DLA forecasting method and two alternatives: exponential smoothing of historical demand, and a program forecast with a smoothed demand-per-program rate. Our findings were as follows:

- Exponential smoothing of historical demand performs better than program-based forecasting.
- Both alternatives outperform the current DLA method.

- Reducing the smoothing constant – that is, placing less emphasis on the most recent quarter's demands, improves the performance of both alternatives.

In addition to having the advantages outlined above, exponential smoothing of historical demand, unlike the program-based method, avoids the complications associated with forecasting demand for items with applications to multiple, dissimilar weapon systems. For all these reasons, we recommend that DLA use exponential smoothing of historical demand instead of its current method.

DLA's Operations Research Office (DORO) is already developing Composite Forecasting, which includes exponential smoothing among its forecasting method choices. Composite Forecasting is intended to replace the current method when the Joint Logistics Systems Center (JLSC) makes the Statistical Demand Forecasting package available to DLA.

The DORO is also developing a method for estimating the effects of weapon system phaseouts on item demands in order to provide guidance to the managers of those items affected. We strongly recommend that this effort continue. Better buy decisions require not only technical improvements to forecasting, but also up-to-date information on management actions that could justify reducing or eliminating certain buys.

Contents

Contents (Continued)

Contents (Continued)

Figures

Figures (Continued)

Tables

CHAPTER 1

Overview

BACKGROUND

The Defense Logistics Agency (DLA)[1] currently bases its forecasts of demand for most consumable weapon system items on historical demand. Management at DLA has been concerned that these forecasts will not respond quickly enough to the decrease in demand for some DLA items occasioned by ongoing reductions in programs and in numbers of units of certain weapon systems. This lack of responsiveness, if present, would cause overly large demand forecasts for some items and lead to unnecessary buys and excess supply.

Program-based forecasting is a natural alternative to demand-based forecasting because of its obvious responsiveness to declines in programs. In the simplest version, the estimated demand for an item is the program for the item's weapon system multiplied by a demand-per-program factor. Thus, if a system's flying hours, say, change by a certain percentage, projected demands for that system's items will change by the same percentage (all else being equal). More sophisticated versions are discussed in the Army studies referenced below.

Earlier studies are inconclusive on the question of whether program-based forecasting is preferable to historical-demand-based forecasting. Extensive DLA work on demand forecasting [1, 2] has not considered program-based forecasts. Army studies [3, 4] have found that certain program-based forecasts outperform moving averages of historical demand on populations of items consisting largely of consumables. On the other hand, one Air Force study of demand forecasting for consumable items [5] found that using a moving average of historical demand was preferable to using a program-based forecast.

We consider three possibilities: program-based forecasts, historical-demand-based forecasts, and a weighted average of these two types of methods.

OBJECTIVES

Our objectives in conducting the study embodied in this report were as follows:

- Determine whether there is a significant correlation between (1) weapon system programs and (2) demand for consumable weapon system items.

[1] Appendix F is a glossary of acronyms used in this report.

- Determine whether there is an alternative forecasting method that offers better inventory performance for a given level of investment than the current (historical-demand-based) method.

- If an alternative forecasting method outperforms the current method, determine whether it is feasible and cost-effective to implement.

Demand Data

We obtained demand histories for consumable items in DLA's Weapon System Support Program (WSSP) whose stock levels are based on demand forecasts; thus we excluded numeric stockage objective and insurance items. We further restricted items to those that were under DLA management prior to 1 January 1990. This eliminated items assumed by DLA under the Consumable Item Transfer Program. After filtering the data, we had 313,838 items, or roughly 70 percent of the 440,000 WSSP items with demand-based forecasts. Each item's demand history covered 36 quarters, spanning the period from FY84 through FY92.

Demand histories were obtained by Service and were separated into nonoverhaul and overhaul demand within each Service. Demands from Foreign Military Sales (FMS) and military assistance programs (MAPs) were excluded, as was other non-Service demand. An item's nonoverhaul and overhaul demand originating from a Service was then further divided into recurring and nonrecurring demand. We focused on recurring demand alone, operating on the assumption that this is the demand that is intrinsically "forecastable."

Program Data

We obtained weapon system densities (the number of units in use) for 94 weapon systems representing all of the Services. Systems included aircraft, helicopters, howitzers, machine guns, mortars, tanks, ships, submarines, and others.

To investigate the possibility that weapon system use and overhaul programs, rather than the number of units in use, drive consumable item demand, we obtained planned flying hour programs from the Army and the Air Force, actual flying hour programs from the Navy, and planned overhaul programs from the Air Force.

Approach

We focused on single-application items, for the study of correlation between item demand and programs and also for the assessment of forecasting methods.

For the correlation analysis, we used total demand for all single-application items of a weapon system, reasoning that it would be less susceptible to large non-program-driven fluctuations than the demand for individual items would be.

In the spirit of "Weapon System Support," we chose to evaluate forecasting methods in terms of inventory performance resulting from a given level of investment. Other measures, such as mean squared error or mean absolute error, provide little indication of the effects on inventory performance of changing a forecasting method. One forecasting method may offer lower mean squared error (averaged across items) but worse inventory performance than another [1, 6].

Forecasting Methods

We focused our evaluation of alternative forecasting methods on exponential smoothing-based techniques. Exponential smoothing is easy to implement, has been shown by a number of studies to be effective, and is familiar to DLA materiel management personnel. We limited the number of alternatives, because our goal was to determine whether DLA can use program information to improve demand forecasts. We began with the assumption that if using program information were able to improve forecasts, then the improvement would be evident in simple as well as complex forecast algorithms.

The methods we analyzed were as follows:

a. Demand proportional to program, where the proportionality is estimated by single exponential smoothing of historical demand per program unit.

b. Single exponential smoothing of historical demand.

c. Weighted combinations of (a) and (b).

d. DLA Standard Automated Materiel Management System (SAMMS) algorithm.

The SAMMS technique was included as a baseline for the analysis. In fact, DLA intends to adopt a different method when the Statistical Demand Forecasting package is made available by the Joint Logistics Systems Center (JLSC). Methods (a) and (b) between them pick up the extremes, [i.e., extensive use of program information in method (a); no use of program in method (b)]. Method (c), the combination of (a) and (b), was added for completeness and also because some previous work had suggested that program information may be beneficial when used as a component of the forecast.

The forecast methods are described in detail in Chapter 4.

Assessing Performance of Forecasting Methods

Previous studies of forecasting methods have used two approaches to ranking them. One approach uses statistical measures such as mean squared error, or mean absolute deviation, for ranking. The problem with this approach is that it does not assess the consequences of underforecasting or overforecasting. Another approach creates a model of the inventory system and produces measures of cost and supply performance. That is, it emulates how the inventory system would perform if a particular forecasting method is used. We prefer this approach, because it uses performance measures that show the effect of the choice of forecasting method on customer support.

We therefore chose to build an inventory system simulation that uses the 36-quarter demand history to produce estimates of wholesale response time and inventory investment for each forecast method. By varying stock levels, we were able to produce curves showing the relationship between wholesale response time and average inventory investment (by response time, here, we mean the average time a demand spends on backorder, averaging across all demands, including those filled immediately). We judged a forecasting method best if it achieved a given response time for the least cost.

Findings

For most of the 94 weapon systems in our sample, *we found only weak-to-moderate correlation* between nonoverhaul demand and weapon system densities, and between total (overhaul and nonoverhaul) demand and densities. For 50 aviation systems, we found low-to-moderate correlation between flying hours and nonoverhaul demand and also between flying hours and total demand. Correlation between planned overhauls of Air Force aircraft and overhaul demands was generally weak.

On charts showing demand and program versus time, the long-term trend in demand, which for many weapon systems paralleled the long-term trend in the weapon system program, was always dominated by short-term fluctuations of much larger magnitude. The duration of demand "spikes" was often on the order of one to two years, comparable to the longest procurement lead-times for items in our sample.

Single exponential smoothing of historical demand resulted in better inventory performance than did density-based (or, where applicable, flying-hour-based) forecasting. Both alternative forecasts performed better than the current DLA method.

Exponential smoothing performed still better when we reduced the smoothing constant from 0.2 to 0.1, which has the effect of giving less weight to the most recent quarter's demand and is more stable.

Conclusions

The program-driven component of demand is small in comparison with demand fluctuations that arise from ordering patterns, maintenance actions, and other unknown factors.

For single-application items, where we might expect program-based forecasting to perform best, single exponential smoothing of historical demand still outperformed program-based forecasting. Accordingly, it is likely that exponential smoothing will also outperform program-based forecasts for multiple-application items. For such items, differing program profiles for each weapon system application, and the likelihood of differing impact on demand across weapon systems even if program changes were parallel, would further attenuate any benefits of a program-based forecast.

Recommendations

We recommend that DLA change its forecasting method for consumable weapon system items to single exponential smoothing of historical demand. The method is requires no additional data, is simple, and is already one of the choices available in the Composite Forecasting methodology that DLA's Operations Research Office (DORO) is developing. Also, DLA should move to a smaller smoothing constant.

CHAPTER 2

Data Base Development

INTRODUCTION

This chapter discusses our data and the processes we used to select and filter that data. The results-oriented reader may wish to skim or skip over this chapter. The analysis is discussed in Chapters 3 and 4; our conclusions and recommendations are in Chapter 5.

ITEM SELECTION

We considered only items in the DLA Weapon System Support Program (WSSP). We refer to these as "weapon system items." These are items that at least one of the Services has asked DLA to consider as an item important to operation or support of a particular weapon system. The DLA Integrated Data Bank (DIDB) identifies an item's weapon system applications with one or more weapon system designator codes (WSDCs).

Limiting ourselves to items for which DLA uses a demand forecast to determine the item's stock level, we considered only items with Supply Status Code 1 (stocked) and Item Category Code 1 (demand-based stockage policy).

To avoid having to eliminate large numbers of items with short demand histories from the data base, we considered only established items (Age of Inventory Code "E") and excluded items whose management was assumed by DLA after 1 January 1990. In particular, this excluded most of the items transferred to DLA from the Services under the Consumable Item Transfer Program. The remaining items constitute about 70 percent of the items in the WSSP that have stock levels based on a demand forecast.

All selection criteria above were applied only to items present in the DIDB during FY93. This means that migration of items across categories before FY93 was not considered.

DEMAND HISTORIES

For the classes of items described above, DORO provided requisition summaries from the DIDB's requisition history file. We obtained separate requisition summaries for requisitions originating at overhaul and nonoverhaul activities

within each Service. Thus an item used only by the Army and Navy would have distinct requisition summaries for requisitions arising from Army nonoverhaul activities, Army overhaul activities, Navy nonoverhaul activities, and Navy overhaul activities. We identified requisitions as belonging to an overhaul or nonoverhaul requisition summary through the DoD Activity Address Codes (DoDAACs) on those requisitions.

Each summary contained the total demand from all requisitions received by DLA from a Service/activity, for each quarter with at least one requisition, during the period from FY84 through FY92. By a demand, we mean the request for a single unit of an item. We converted each item's requisition summary to a demand history consisting of a national stock number (NSN) followed by 36 quarters of demands. (Zero demand is a permissible value.) Demands in each quarter were further divided into recurring and non-recurring demands.

We excluded demand from all types of FMS, MAPs, and other non-Service activities from our demand histories.

The number of items present in each demand history is shown in Table 2-1. In general, each item was present in more than one of these demand histories.

Table 2-1.
Number of Items in Demand Histories

Service/activity	Number of items
Air Force nonoverhaul	191,507
Air Force overhaul	132,694
Army nonoverhaul	155,816
Army overhaul	100,307
Navy nonoverhaul	255,159
Navy overhaul	179,260
Marine nonoverhaul	82,360
Marine overhaul	52,458

ITEM CHARACTERISTICS

We obtained both time-phased and non-time-phased item characteristics files containing item prices, production and administrative lead-times, and other item characteristics. All non-time phased data were taken from FY93.

Application Files

We obtained item application data from the DIDB, with one record for each combination of NSN, WSDC, and Weapon System Essentiality Code. From this, we extracted an application file consisting of records with unique NSN-WSDC combinations and containing the highest essentiality code for each such application. From the application file, we created a file showing the number of applications for each NSN, and from that, we developed a list of the single-application items, containing 170,899 NSNs.

Single-Application Item Demand Histories

By matching the Service/activity demand histories against the list of single-application items, we obtained Service/activity demand histories for single-application items only. The number of items present in each of these histories is shown in Table 2-2.

Table 2-2.
Number of Single-Application Items in Demand Histories

Service/activity	Number of items
Air Force nonoverhaul	21,471
Air Force overhaul	20,562
Army nonoverhaul	26,079
Army overhaul	13,459
Navy nonoverhaul	38,970
Navy overhaul	29,693
Marine nonoverhaul	13,256
Marine overhaul	7,409

Note: These numbers are for the filtered data bases. Data filtering is described below.

Totaling demand for all single-application items applying to a weapon system yielded demand histories by weapon system for each Service/activity combination. Table 2-3 displays the number of weapon systems present in each demand history.

In each Service/activity demand history, we identified some items whose WSDCs indicated other Services (the third position of the WSDC identifies the Service that requested the items' inclusion in the WSSP). When the weapon system identified by the WSDC was identical to or substantially similar to a weapon system used by the Service, we retained the item's demand history; otherwise, we discarded it. The number of items thus eliminated was in the range of 50 to

100 for the nonoverhaul demand histories and 100 to 400 for the overhaul demand histories.

Table 2-3.
Number of Weapon Systems in Single-Application Demand Histories

Service/activity	Number of weapon systems
Air Force nonoverhaul	32
Air Force overhaul	32
Army nonoverhaul	28
Army overhaul	28
Navy nonoverhaul	52
Navy overhaul	54
Marine nonoverhaul	7
Marine overhaul	7

Note: The difference in the number of weapon systems in the Navy nonoverhaul and overhaul data bases is due to the fact that we had no single-application item demand in the nonoverhaul data base for two weapon systems that appeared in the overhaul data base.

The presence of these items tells us that the application data used to identify single-application items are not always reliable – for instance, an item identified in the application data as applying only to a battleship does not belong in a demand history of items applying only to Army systems. Any DLA project (such as the Multi-link inventory management system now under development) relying on DLA's application data will require improvement of the data.

The filtered histories of total single-application item demand by weapon system were used in the correlation analysis described in Chapter 3; the filtered item-level demand histories for single-application items were used in the analysis of forecasting methods described in Chapter 4.

Program Data

We used four types of program data: actual weapon system densities (the number of units of a system), planned and actual flying hours for aviation systems, and planned overhauls of aviation systems. Each is discussed below.

We obtained histories of weapon system densities from the Office of the Secretary of Defense, Program Analysis and Evaluation (OSD, PA&E). Histories extended from FY92 back to FY84 (or less, if only limited data were available). For each system, every effort was made to identify the number of units actually in use, rather than the total number in existence. Our density histories covered about 120 weapon systems, representing all Services, and included aircraft,

helicopters, howitzers, mortars, ships, submarines, one type of strategic missile, tanks, and trucks. Where substantially similar systems were used by two Services, we added their densities together.

For systems for which the first two years of data were missing, but that had a slowly changing series of densities, we set the missing densities to the density in the first quarter for which data were available. When more than two years of data were missing, or where the density increased or decreased sharply from that in the initial quarter with data, we dropped the system from our sample. This process left us with density histories for 94 weapon systems. We then converted yearly densities to quarterly densities via linear interpolation.

We obtained planned flying hours for FY84 through FY92 from Headquarters Air Force, Office of the Deputy Chief of Staff for Plans and Operations (specifically AF/XOOT), where the flying hour programs were those as of the beginning of the fiscal year for which they were programmed. Flying hours by mission design series (MDS) were aggregated to yield flying hours by mission design (MD) whenever the WSDCs in our application data referred only to an MD. After aggregation, and after deletion of the B-2 (for lack of data), we had planned flying hours for 23 types of aircraft and helicopters.

The Army's Deputy Chief of Staff for Operations and Plans (DCSOPs) (DAMO-TR) provided us with programmed flying hours for FY84 through FY92, where the flying hours were programmed in the Program Budget Execution Review. We received densities for 28 types of helicopters and aircraft. After aggregating flying hours for weapon systems with common WSDCs and deleting systems for which we had no single-application item demand in our data base, 6 systems remained.

The Navy's Flying Hour Office provided us with a history of actual flying hours by fiscal year for the period from FY88 through FY92. Navy flying hours include those of Marine aircraft. We aggregated flying hours in cases where DLA identified two or more type mission series (TMSs) by the same WSDC. This left us with flying hours for 21 types of aircraft and helicopters.

We converted flying hours from each Service from yearly to quarterly figures, using linear interpolation.

The Air Force Material Command (LGIR) provided us with planned overhauls for each MDS, by quarter, for FY87 through FY92. Planned overhauls for a given fiscal year were those approved in the Logistics Support Review, held in the spring before the beginning of the fiscal year. Where DLA identified two or more MDS's with the same WSDC, we aggregated the planned overhauls, yielding histories of planned overhauls for 24 types of aircraft and helicopters.

CHAPTER 3

Analysis of Demand and Programs

In our investigation of the relationship between demands and programs, we focused on single-application items. If a significant correlation emerged here, we planned to extend our analysis to items with two to five applications. If we did not see a strong correlation with single-application items, we thought it reasonable to forgo correlation tests for multiple-application items, for the following reason: unless demands arising from each of an item's applications have equally strong program-correlated trends (unlikely), a strong program-correlated trend in demand from one weapon system would be diluted by stable or even opposite-trending demand arising from other weapon systems.

To quickly see the relationship, if any, between demands and programs, we chose graphical analysis. In each type of chart discussed, "total demand from a weapon system" refers to the time series consisting of 36 quarters of total demand for single-application items on a weapon system. "Weapon system program" refers to the time series consisting of 36 quarters of the weapon system program. Our charts consisted of

- time charts – graphs of both total demand from a weapon system and weapon system program as functions of time, on a single chart;
- scatter plots – graphs of total demand from a weapon system versus weapon system program;
- correlation charts – graphs of the cross-correlation between total demand from a weapon system and the weapon system program, as a function of the lag between the two time series.

Time charts enabled us to look for parallel trends in programs and demands over time. Scatter plots provided visual evidence for or against a functional relationship between program and demands: if points on the scatter plot clustered about the best-fit regression line, this would suggest a linear relationship; if they clustered about a curve, it would suggest a non-linear relationship, and if they clustered about vertical or horizontal lines, it would suggest no relationship. Correlation charts showed the extent to which demands and lagged densities fit a linear relationship.

We considered the correlation between two time series with a given lag "significant" if there was at least a 95 percent probability that the observed correlation could not have occurred between two time series generated by jointly distributed, normal random variables. We produced correlation bar charts, where the height of each bar represented the correlation for a given lag. Two significance curves, one lying below the horizontal (lag) axis and one above,

showed significance limits for the correlation bars: if a bar indicating positive correlation extended above the upper significance curve, the correlation indicated by that bar was significant (as defined above); if a bar indicating negative correlation extended below the lower significance curve, the correlation was significant; if bars either above or below the axis lay between the significance curves, the correlation was not significant.

ANALYSIS OF DEMANDS AND DENSITIES

We first examined the relationship between weapon system densities and nonoverhaul demand (see Appendix A). We had a total of 94 weapon systems with density histories.

Our time charts showed that for virtually every weapon system, the magnitude of demand "peaks" and "troughs" dwarfed the longer term trend in demand over periods of two years or less (for example, see Figure 3-1). Since procurement lead-times for most of our items were on the order of six months to a year, it was unlikely that the demand for an item at the time a shipment arrived would be anywhere near the demand predicted at the time the shipment was ordered, regardless of the forecasting method. There were also cases where density was constant but demand varied widely (see Figure 3-2).

Examining the scatter plots of density versus nonoverhaul demand, we found that for most weapon systems the points were widely dispersed about the regression line. In some cases, the points formed an inverted "T" or sideways "L" pattern, so that there were many points with the same density but with widely varying demands (see Figures 3-3 and 3-4).

These scatter plots showed that a strong linear relationship between density and demand occurred for relatively few systems and that there were many cases in which there was clearly no functional relationship, linear or non-linear, between density and demand.

To quantify the correlation between density and demand and to test the effect of a time lag, we examined cross-correlation charts. When we refer to correlation, we mean the maximum correlation between the nonoverhaul demand time series and the lagged density time series, where the lag between densities and demands ranges from 0 to 7 quarters. Our results are displayed in Table 3-1.

Nearly two-thirds of the weapon systems show no significant correlation (as defined above) between density and demand, or show negative correlation. In the cases where the correlation was not significant, it was also typically on the order of 0.3 or less. Only a quarter of the systems exhibit a correlation of 0.5 or better. We concluded that weapon system density is generally not a good indicator of nonoverhaul demand.

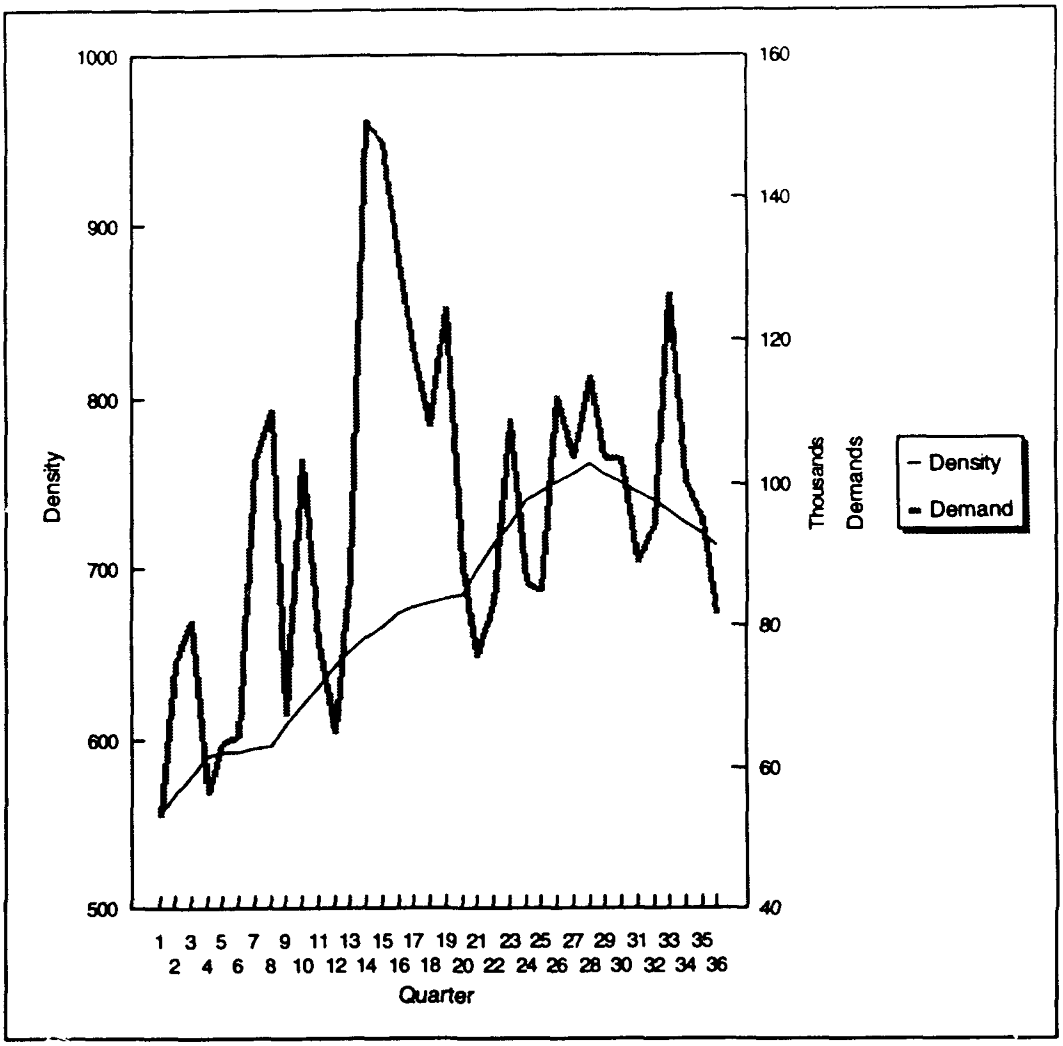

Figure 3-1.
F-15 Eagle: Nonoverhaul Demand and Density by Quarter

Next we examined the relationship between total (nonoverhaul plus overhaul) demand and weapon system densities (see Appendix B). Time charts again showed a pattern of large amplitude variations in demand relative to the demand trend. On the scatter plots, we noticed that for the few weapon systems that had points clustered about the regression line, the points now clustered more tightly, indicating stronger correlation. But for the roughly 60 percent of the systems that had shown no clear relationship between nonoverhaul demand and density, there was no better relationship with total demand and density. The correlation results shown in Table 3-2 confirm this.

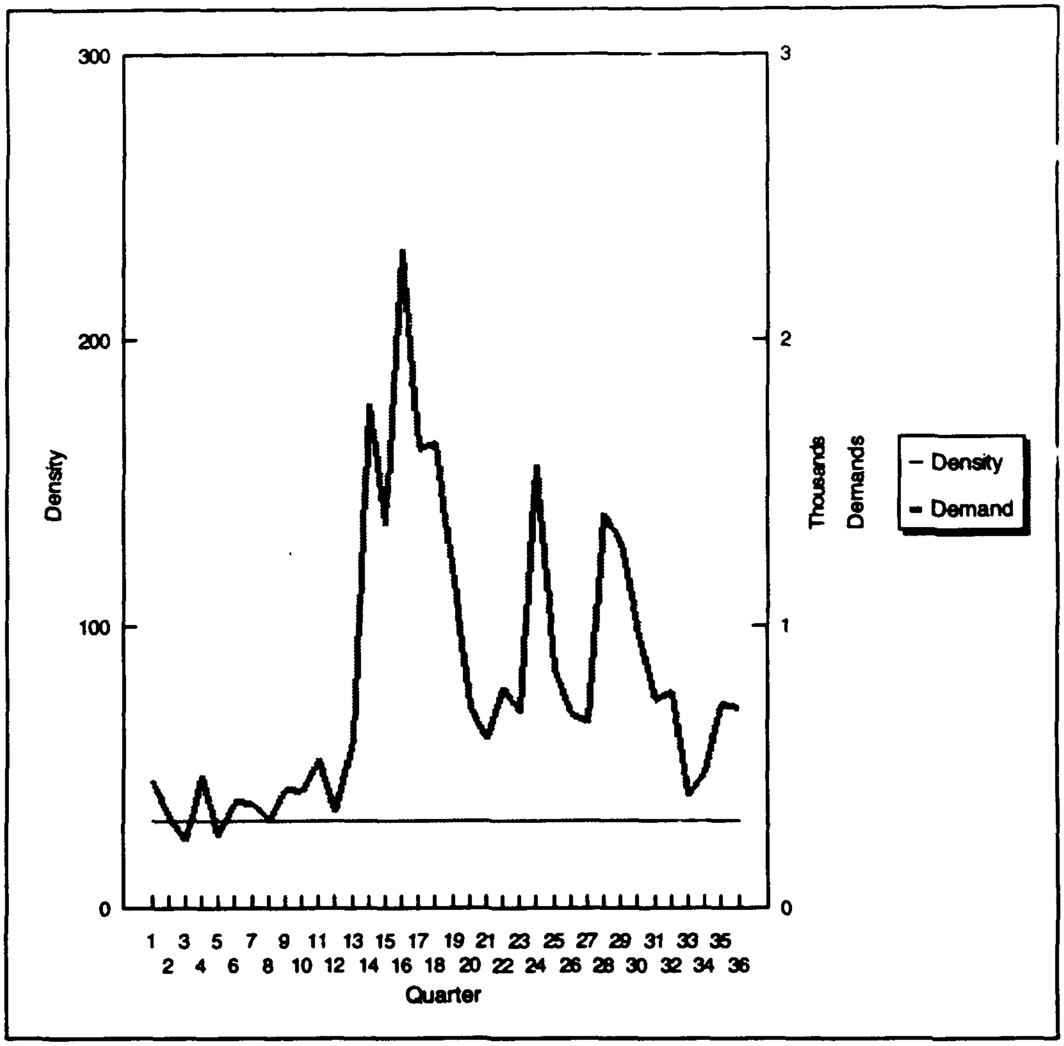

Figure 3-2.
***Spruance*-Class Destroyers: Nonoverhaul Demand and Density by Quarter**

For a few systems, such as the F-16, there was strong (greater than 0.8) correlation between density and demand (see Figure 3-5), but this is far from typical. For most weapon systems (and therefore most single-application items), density was not a good indicator of total demand, as in the case of the *Sturgeon*-class submarine (see Figure 3-6).

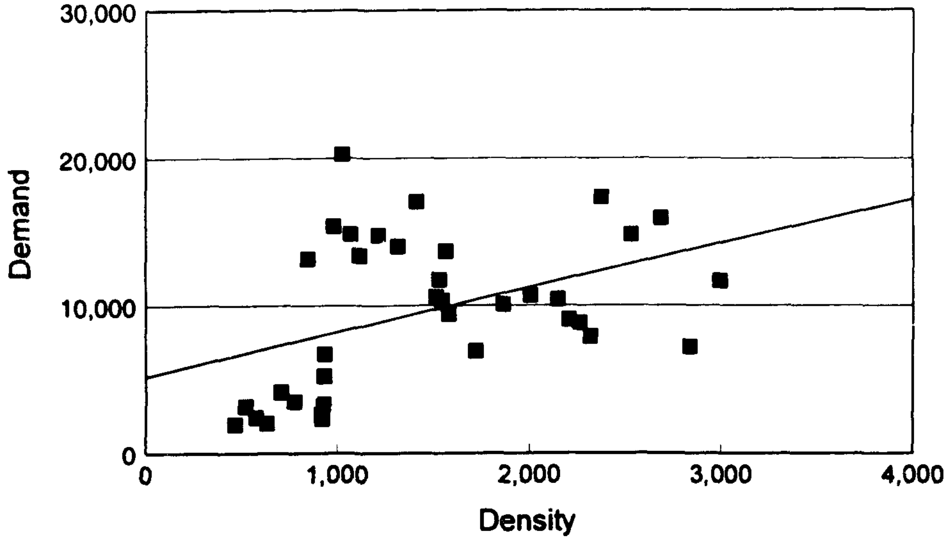

Figure 3-3.
Scatter Plot of Bradley Fighting Vehicle Demand versus Density

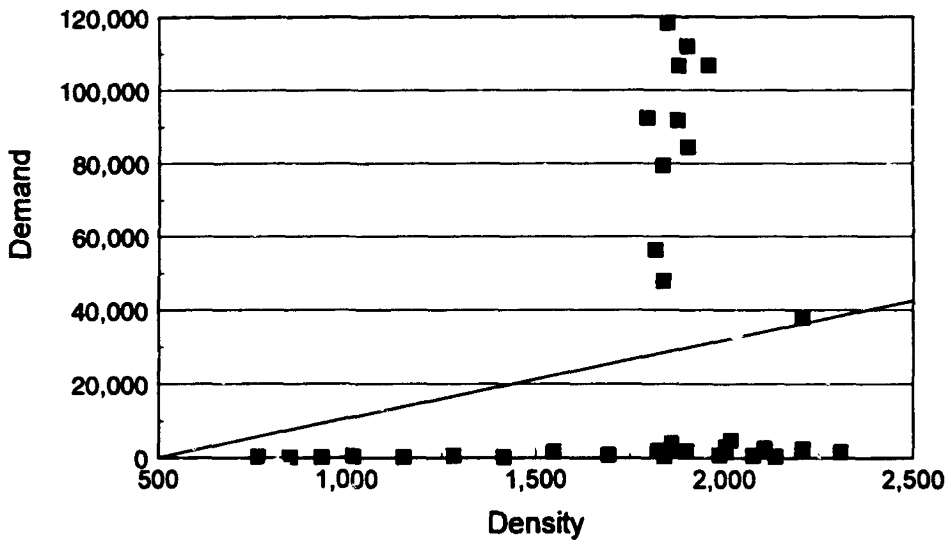

Figure 3-4.
Scatter Plot of M-1 Tank Demand versus Density

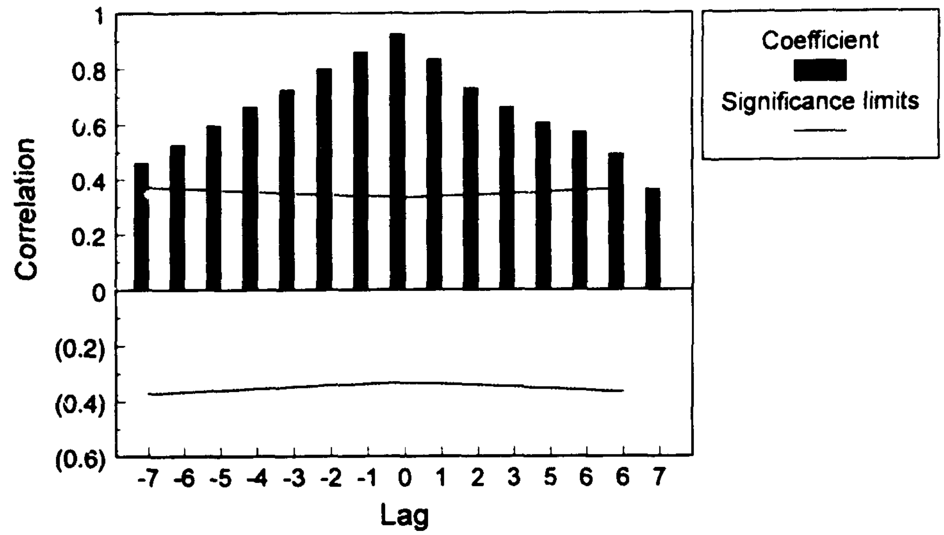

Figure 3-5.
F-16 Fighting Falcon: Correlation of Total Demand with Density as a Function of the Lag Between Time Series

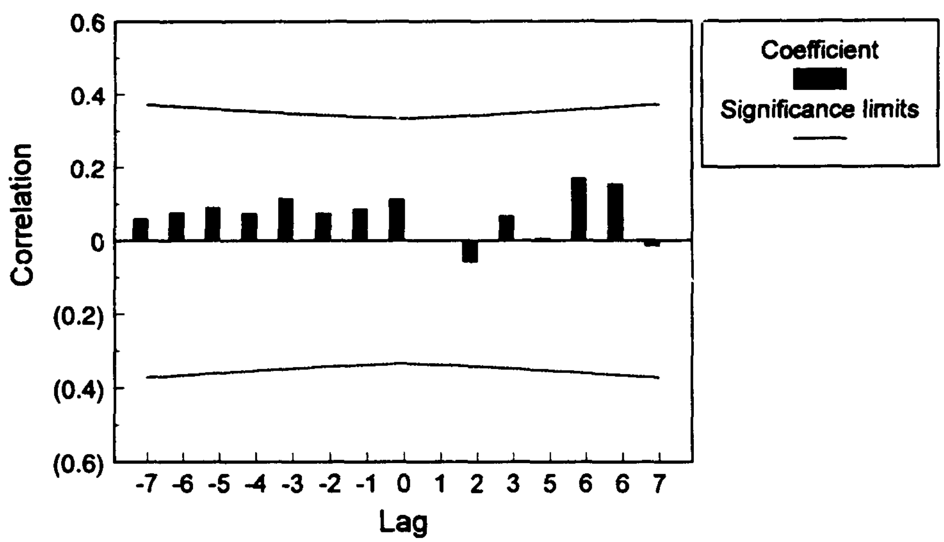

Figure 3-6.
Sturgeon-Class Submarine: Correlation of Total Demand with Density as a Function of the Lag Between Time Series

Table 3-1.
Correlation Between Nonoverhaul Demand and Density

Maximum correlation	Number of systems	Percentage of systems
Not significant, or negative	58	62
0 < correlation < 0.4	4	4
0.4 ≤ correlation < 0.5	8	9
0.5 ≤ correlation < 0.6	7	7
0.6 ≤ correlation < 0.7	10	11
0.7 ≤ correlation < 0.8	4	4
0.8 ≤ correlation < 0.9	3	3

Table 3-2.
Correlation Between Total Demand and Density

Maximum correlation	Number of systems	Percentage of systems
Not significant, or negative	58	62
0 < correlation < 0.4	3	3
0.4 ≤ correlation < 0.5	8	9
0.5 ≤ correlation < 0.6	8	9
0.6 ≤ correlation < 0.7	9	10
0.7 ≤ correlation < 0.8	5	5
0.8 ≤ correlation < 0.9	2	2
0.9 ≤ correlation < 1.0	1	1

Note: **Percentages sum to more than 100 percent because of rounding.**

Analysis of Demands and Flying Hours

To see whether there was a stronger relationship between weapon system use and demand than the one we found between densities and demand, we repeated our analysis for 50 aviation systems, substituting flying hours for densities. For Army and Air Force aircraft, we obtained programmed flying hours; the Navy supplied us with actual flying hours.[1] We considered separating weapon systems into two categories on the basis of planned versus actual flying hours, but as the results emerged, they were of essentially the same character for both subgroups. For this reason, results for aviation systems from the three Services are displayed together in Tables 3-3 and 3-4. (See also Appendices C and D.)

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[1] Also, the Navy data spanned 20 quarters instead of 36.

We conducted separate analyses for nonoverhaul demand and for total demand. In both cases, our observations were similar to those we had made with densities. On time charts, there were large variations in demand relative to any trend that paralleled the flying hour program, and on scatter plots, points were widely dispersed about the regression line for most systems.

With the correlation charts, we found only minor differences between the results for nonoverhaul demand and those for total demand: the percentage of weapon systems with insignificant or negative correlation was slightly lower for nonoverhaul demand than it was for total demand (50 percent versus 52 percent), while the number with correlation between 0.5 and 0.7 was higher for total demand (22 percent versus 17 percent). The number of systems with strong correlation (greater than 0.7) was 12 for nonoverhaul demand and 14 for total demand. Tables 3-3 and 3-4 display our results for correlation of flying hours with nonoverhaul demand and total demand, respectively. We concluded that there was no clear advantage to splitting out nonoverhaul demand for the purpose of finding a relationship between demand and flying hours.

Table 3-3.
Correlation Between Nonoverhaul Demand and Flying Hours

Maximum correlation	Number of systems	Percentage of systems
Not significant, or negative	25	50
0 < correlation < 0.4	2	4
0.4 ≤ correlation < 0.5	8	16
0.5 ≤ correlation < 0.6	8	16
0.6 ≤ correlation < 0.7	1	1
0.7 ≤ correlation < 0.8	3	6
0.8 ≤ correlation < 0.9	3	6
0.9 ≤ correlation < 1.0	0	0

Note: Percentages sum to more than 100 percent because of rounding.

Comparing our flying hour correlation results with those we obtained with densities, we find a slightly higher percentage of systems (12 to 14 percent versus about 8 percent) with strong correlation (greater than 0.7 percent). The percentage of systems with moderate correlation (0.5 to 0.7) lay in the range of 17 to 22 percent for both flying hours and densities. We concluded that the relationship between demands and flying hours was not significantly stronger than that between demands and densities.

Table 3-4.
Correlation Between Total Demand and Flying Hours

Maximum correlation	Number of systems	Percentage of systems
Not significant, or negative	26	52
0 < correlation < 0.4	2	4
0.4 ≤ correlation < 0.5	4	8
0.5 ≤ correlation < 0.6	7	14
0.6 ≤ correlation < 0.7	4	8
0.7 ≤ correlation < 0.8	4	8
0.8 ≤ correlation < 0.9	2	4
0.9 ≤ correlation < 1.0	1	2

ANALYSIS WITH OVERHAUL DEMANDS AND PROGRAMMED OVERHAULS

We originally split demand into nonoverhaul and overhaul demand to determine whether there were stronger relationships between nonoverhaul demand and flying hours, and between overhaul demand and programmed overhauls, than were present with total demand and with flying hours. Although the results of the previous section show that there that the correlation between nonoverhaul demand and flying hours was not significantly better than that between total demand and flying hours, we present our overhaul demand results because we believe that they are of interest in their own right.

For overhaul demands and programmed overhauls (see Appendix E), we considered only correlation charts. We examined 24 Air Force weapon systems for which we were able to obtain programmed overhauls. As shown in Table 3-5, for three quarters of the weapon systems, the correlation between programmed overhauls and overhaul demands was either insignificant or negative. For the remaining one-quarter of the weapon systems, we observed moderate correlation (0.5 to 0.7). The lack of a strong correlation here may indicate that actual and planned overhauls differ substantially, as a result of work load scheduling and budgeting. It may also be true that it is not the number of weapon system overhauls that drives overhaul demand. In particular, many overhaul demands for consumables arise from overhauls of reparable items rather than from overhauls of a complete weapon system. But an investigation of the relationship between programmed overhauls of reparable items and consumable item demand would have required a data collection effort beyond the scope of this study.

Table 3-5.
Correlation Between Overhaul Demands and Programmed Overhauls

Maximum correlation	Number of systems	Percentage of systems
Not significant, or negative	18	75
0 < correlation < 0.4	0	0
0.4 < correlation < 0.5	0	0
0.5 < correlation < 0.6	5	21
0.6 < correlation < 0.7	0	0
0.7 < correlation < 0.8	1	4
0.8 < correlation < 0.9	0	0
0.9 < correlation < 1.0	0	0

SUMMARY

Whether the program data covered weapon system densities, flying hours, or overhauls, for most weapon systems we found only a weak-to-moderate correlation between demands and programs. Segregation of demand into nonoverhaul and overhaul categories did not reveal a stronger relationship between demands and the relevant type of program data.

CHAPTER 4

Analysis of Forecasting Methods

In this chapter, we discuss the forecasting methods that we decided to evaluate, the method of evaluation, and the results of the evaluations, using both density and flying hours as programs. Most of our analysis was concerned with the performance of forecasting methods, but we also considered implementation issues.

PROGRAM-BASED FORECAST

When the Services use program information (such as density or flying hours), to forecast demand, demand is assumed to be proportional to the program. Our program-based forecast technique makes the same assumption. The burden of the forecasting algorithm, then, is to estimate the size of the proportionality.

For a given item, let

FP(n, j) = program-based forecast of demand for quarter j made at the beginning of quarter n; $j \geq n$,

D(n) = demand in period n,

P(n) = program in period n,

α = smoothing constant, $0 < \alpha < 1$,

SSFDP(n) = single exponentially smoothed value of the observations $D(j)/P(j)$, $j = 1, 2 \ldots n$,

$$= \alpha \frac{D(n)}{P(n)} + (1 - \alpha)\, SSFDP(n-1),\ n \geq 1. \qquad \text{[Eq. 4-1]}$$

Then,

$$FP(n, j) = P(j) * SSFDP\,(n-1). \qquad \text{[Eq. 4-2]}$$

Demand-Based Forecast

Currently, DLA uses a pure demand-based forecast. However, because this technique has some unconventional features (these are explained later), we decided to use single exponential smoothing of demand, in addition to the DLA method, as counterparts to the program-based method.

If

FD(n, j) = demand-based forecast of demand for quarter *j* made at the beginning of quarter n; $j \geq n$, and

SSFD(n) = single exponentially smoothed value of the observations D(j), j - 1, 2 . . . n,

$$= \alpha D(n) + (1 - \alpha) SSFD(n - 1), \quad \text{[Eq. 4-3]}$$

then

$$FD(n, j) = SSFD(n - 1). \quad \text{[Eq. 4-4]}$$

In this case, the demand forecast for all future quarters is the same. Forecasts change each quarter, depending on the preceding quarter's demand and the previous forecast.

Combination Forecast

Some studies have suggested [3, 7] that program information may be more effective if used in a linear regression scheme. Doing so can have the effect of limiting the impact of program on the forecast. Since our data do not display strict proportionality of demand to program but do indicate some correlation, we also evaluated a weighted combination of the program-based and demand-based forecasts.

Let

FC(n, j) = combination forecast of demand for quarter *j* made at the beginning of quarter n; $j \geq n$, and

w = weight, $0 \leq w \leq 1$.

Then,

$$FC(n, j) = w\, FP(n, j) + (1 - w)\, FD(n, j). \quad \text{[Eq. 4-5]}$$

DLA SAMMS FORECAST

This method is a variant of exponential smoothing, accompanied by a tracking signal to detect the presence of a trend or shift in the demand process. It is unconventional in its use of both single and double exponential smoothing to forecast demand.

Let

FS(n, j) = SAMMS forecast of demand for quarter j made at the beginning of quarter n; $j \geq n$, and

DSFD(n) = double smoothed value of the observations D(j), j = 1, 2 . . . n,

$$= \alpha \, \text{SSFD}(n) + (1 - \alpha) \, \text{DSFD}(n). \qquad \text{[Eq. 4-6]}$$

Then, apart from adjustments to be discussed later,

$$\text{FS}(n, j) = 2\,\text{SSFD}(n-1) - \text{DSFD}(n-1). \qquad \text{[Eq. 4-7]}$$

The SAMMS method can be traced to R.G. Brown [8], who showed that SSF(D, n) - DSF(D, n) corrects for a lag in SSF(D, n) when the demand process has a linear trend. When demand is stationary, E[SSF(D, n) - DSF(D, n)] = 0, so that E[FS(n, j)] = E[SSF(D, n - 1)], where E(X) denotes the expected value of the random variable X. However, FS(n, j) is more sensitive to most recent demand than is single exponential smoothing with the same smoothing constant and is thus more unstable.

As noted previously, some adjustments are made to the basic FS(n, j). First, a tracking signal is computed to detect whether the underlying demand rate is shifting or has shifted in some manner.

If

ASFE(n) = algebraic sum of forecast errors at the end of quarter n

$$= \sum_{j=1}^{n} [F(j, n) - D(j)],$$

MAD(n) = mean absolute deviation of forecast error at the end of quarter n

$$= \alpha |F(n, n) - D(n)| + (1 - \alpha) \, \text{MAD}(n-1), \text{ and}$$

α = smoothing constant, same value as used in Equation 4-5, then the tracking signal (TS), is

$$TS(n) = \frac{ASFE(n)}{MAD(n)} . \qquad \text{[Eq. 4-8]}$$

When the tracking signal exceeds a specified limit twice in a row in the same direction, then the underlying demand rate is assumed to have shifted. To correct for this shift, SAMMS then employs a "correcting α" in Equation 4-7 that is larger than the normal α. This larger value of α has the effect of giving more weight to recent demands. The correcting α is never used more than twice in a row, even if the tracking signal continues to indicate a shift.

Another adjustment is made if FS(n, j), as computed by Equation 4-7, is < 1. Then, SAMMS uses a two-quarter moving average in its place. If the moving average is also < 1, then the quarterly forecast is set to 1.

SAMMS also has logic for dealing with non-recurring demands; we will not discuss this logic, since we have confined our analyses to recurring demand.

Forecast Evaluation Methodology

There are two basic ways to evaluate forecast methods, both of which have been used in previous studies. One way is to compare statistical measures such as mean squared error or mean absolute error for each forecast method. The other way, and the one we prefer, is to compare the methods by simulating their effects on the operational environment. To do this, we constructed a simulator using the quarterly demand history and a simple inventory policy to produce, for each forecast, a trade-off curve of inventory investment versus wholesale response time. We could then evaluate each method in terms of the cost required to achieve a given response time.

Because of data constraints, we kept our simulator as simple as possible. Since we had quarterly demand quantity only, we decided to simulate an inventory policy that reviews assets and stock levels quarterly to determine buy actions. In practice, of course, DLA makes reorder point reviews more frequently than quarterly. Nevertheless, we believe that assuming a quarterly review is reasonable and that running the model using more frequent reviews would not change the relative ranking of forecast methods. The reorder policy was of the reorder level, order-up-to level form – that is, when assets (on-hand plus on-order) drop below the reorder level, an order is placed to bring assets to the order-up-to level.

Because we were testing program-based forecast methods where each future quarter can have a different forecast value, we had to build the stock levels in a manner that would recognize the potential for these forecasts to change. The

reorder level, at the beginning of quarter n, R(n), was set to the expected demand in the procurement lead-time plus a safety level. For simplicity, the procurement lead-time was an integer number of quarters, NP. We have

$$R(n) = \left[\sum_{j=n}^{n+Np-1} F(n, j) \right] + SL(n), \qquad \text{[Eq. 4-9]}$$

where

F(n,j) = forecast of demand for quarter j made at the beginning of quarter n, and

SL(n) = safety level at quarter n.

SL(n) was set using the Presutti-Trepp model that DLA currently uses. Forecast error is required by the model to set the safety level. Instead of the DLA forecast error estimate, which is based on the actual item forecast error history, for simplicity we used the Army variance estimation procedure. This procedure uses an empirically based table that relates forecast error and the item demand frequency. The higher the frequency, the smaller the error [9].

The order-up-to level, S(n), was set to be an integer number of quarters, NQ, of demand above the reorder point. NQ is typically referred to as the procurement cycle. Thus, we set

$$S(n) = R(n) + \sum_{j=n+NP}^{n+NP+NQ-1} F(n, j). \qquad \text{[Eq. 4-10]}$$

In order to produce the tradeoff curves of inventory investment versus response time, we varied the safety level by changing the "lambda factor" or backorder cost used in the Presutti-Trepp model. As the lambda increases, safety levels increase, causing an increase in on-hand inventory and a reduction in the response time. In practice, when seeking to adjust inventory investment or supply performance, the normal method is to adjust the safety level.

The first four quarters of the simulation were used for start-up purposes and were simulated identically for each method tested. On-hand and on-order inventory at the beginning were set to theoretical steady-state average values based on the demand rate over the entire demand history. Simulation then began by processing the quarterly demand history. At the end of each quarter, the simulation did the following:

a. Computed end-of-quarter on-hand inventory by subtracting the quarter's demand from beginning-of-quarter on-hand; negative values denoted backorders.

b. Computed beginning-of-next-quarter on-hand inventory by adding arrivals from procurement to end-of-quarter on-hand inventory and updated on-order; separate variables were maintained for beginning on-hand inventory and ending on-hand inventory.

c. Recomputed the forecast of demand and used it to recompute stock levels.

d. Scheduled a buy to arrive one procurement lead-time in the future and updated on-order if assets (on-hand plus on-order) were below the reorder point.

e. Proceeded to next quarter.

For the first four quarters, the forecasted demand is updated using single exponential smoothing, no matter what forecast method is being evaluated. Forecasts from the specific method do not begin until quarter 5. In addition, to lessen the chance that the initial inventory generated during the first four quarters will unduly influence the results, safety levels are set to zero until the specific forecast method takes effect. Since the specific method cannot have an effect on on-hand inventory or backorders until at least a procurement lead-time from when it is first used, no statistics are accumulated until then.

When simulation is completed for each item, there is a record of on-hand inventory (beginning and ending) for each quarter. These on-hand levels are used to compute average dollars of inventory on-hand and average backorders, under the assumption that demand in each quarter occurs uniformly, (i.e., if demand in the quarter is 180, then it is assumed to occur at the rate of two per day). Response time is defined as the average time a demand spends on backorder, including situations in which the demand is filled immediately, (i.e., time on backorder equal to zero). Response time was not observed directly but was inferred from average backorders using Little's theorem ($L = \lambda w$). In this case, L is average backorders, λ is the demand rate, and w is the response time. When all items are simulated for a specific method and safety level policy, response time is computed by dividing average backorders accumulated over all items by total demand for all items and then converting to days.

FORECASTING PERFORMANCE

Since our correlation analyses indicated that total recurring demand had higher correlation to program, (either flying hours or density), than did recurring nonoverhaul demand, we tested forecast methods on total recurring demand only. We had density data on 94 weapon systems for all Services and planned flying hour data on 28 types of aircraft from the Army and the Air Force (because the flying hours supplied by the Navy were actual flying hours and covered only

20 quarters, we excluded them from this analysis). Separate sets of runs were made for both types of programs.

Instead of separately analyzing each system, we grouped systems according to their program pattern. We found that there were four patterns: stable, increasing, decreasing, and what we called "up and down," to denote an increasing pattern followed by a period of stability and then a decrease.

For all simulation runs, we set the order-up-to level to two quarters of demand above the reorder point and the procurement lead-time to four quarters. DLA's current dollar weighted average for the lead-time is 10.2 months; the procurement cycle averages 7.7 months.

DENSITY FINDINGS

Table 4-1 shows the number of weapon systems in each density pattern group, along with the associated number of parts on those systems on which the forecast methods were evaluated.

Table 4-1.
Weapon-System Density Groups

Group type	Number of systems	Number of parts simulated
Stable	23	2,708
Increasing	25	5,239
Decreasing	30	6,200
Up and down	17	8,770
Total	95	22,917

Figures 4-1 through 4-5 are the response-time versus inventory cost curves for the total set of weapon systems and for each of the four pattern groups. The performance difference between the SAMMS forecast and the two other forecasts may be larger in our simulation than it would be in practice, because the simulation employs quarterly – rather than continuous – review of the inventory position.[1]

[1] A continuous-review inventory system, which DLA uses, permits several orders to be placed during a quarter in which demand increased sharply. These orders would be based on the forecast made at the end of the most recently completed quarter and would therefore be smaller than if they were based on the new, larger forecast made at the end of the current quarter. Hence the inventory cost for a given level of supply performance tends to be less in a continuous-review system, possibly resulting in a narrowing of the performance differences between forecasting methods.

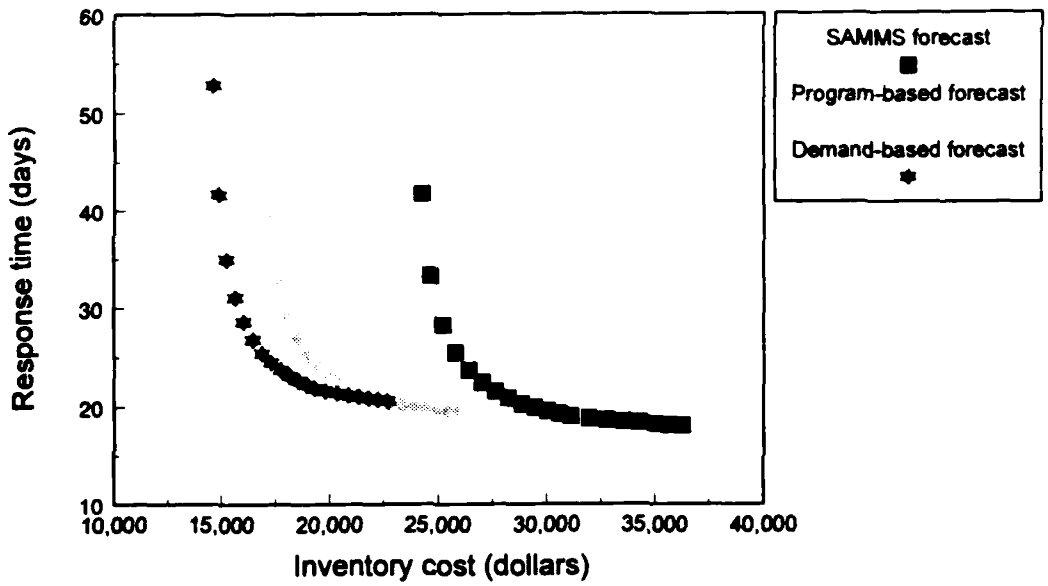

Figure 4-1.
Response Time as a Function of Inventory Investment for All Items on Systems with Density Data

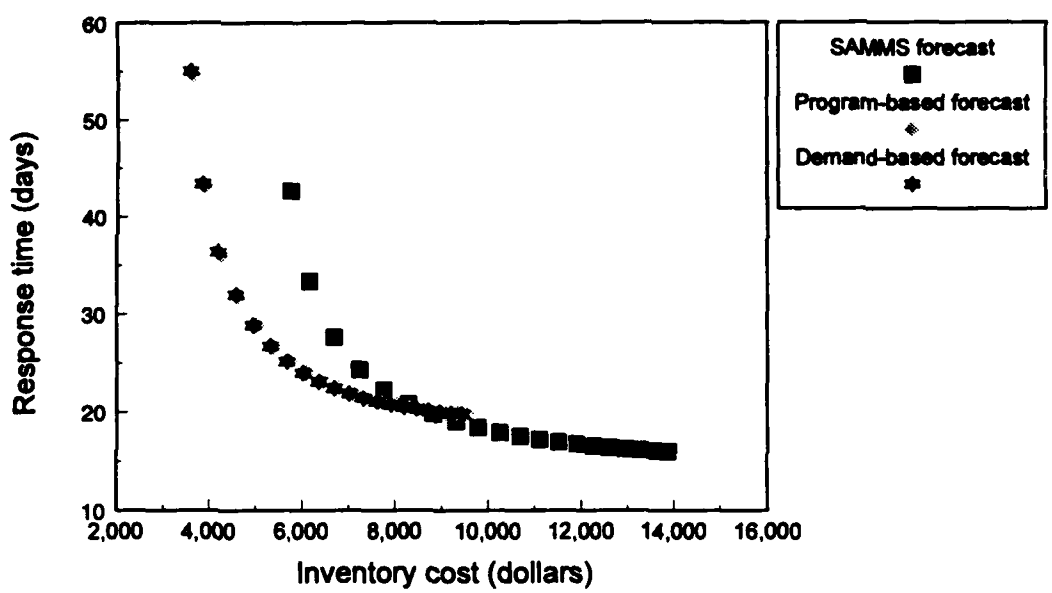

Figure 4-2.
Response Time as a Function of Inventory Investment for Items on Stable-Density Systems

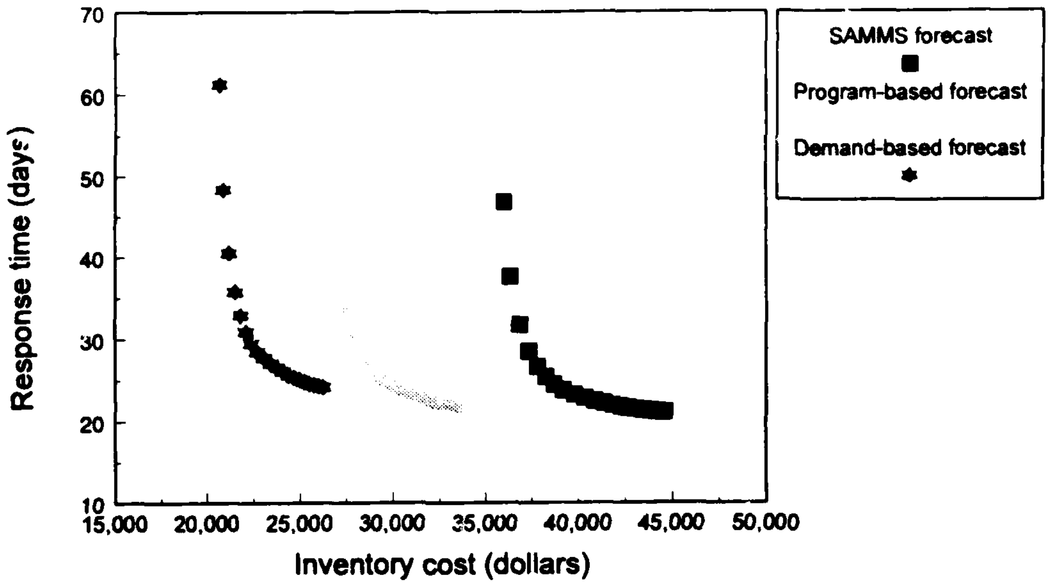

Figure 4-3.
Response Time as a Function of Inventory Investment for Items on Increasing-Density Systems

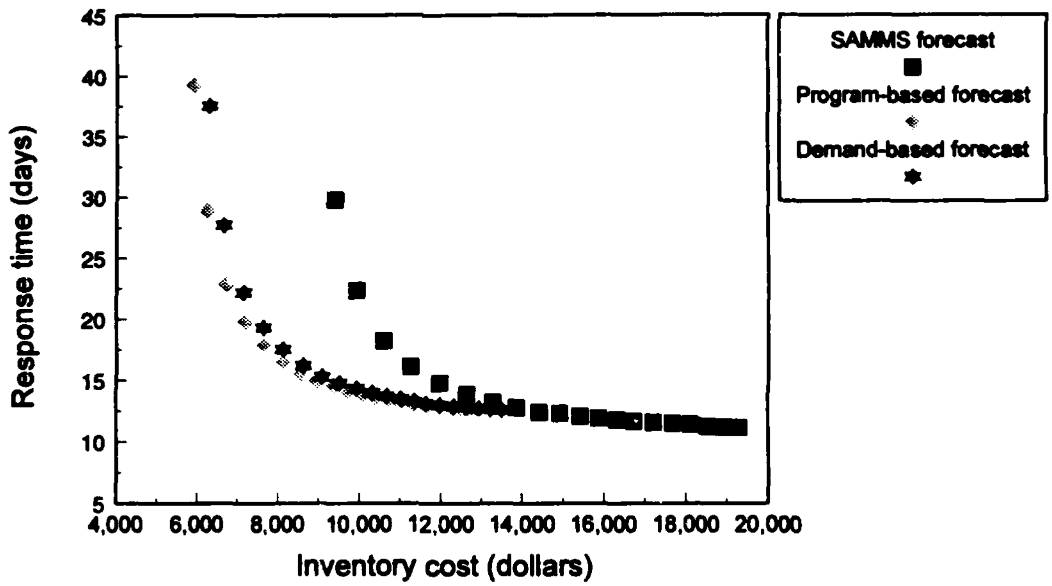

Figure 4-4.
Response Time as a Function of Inventory Investment for Items on Decreasing-Density Systems

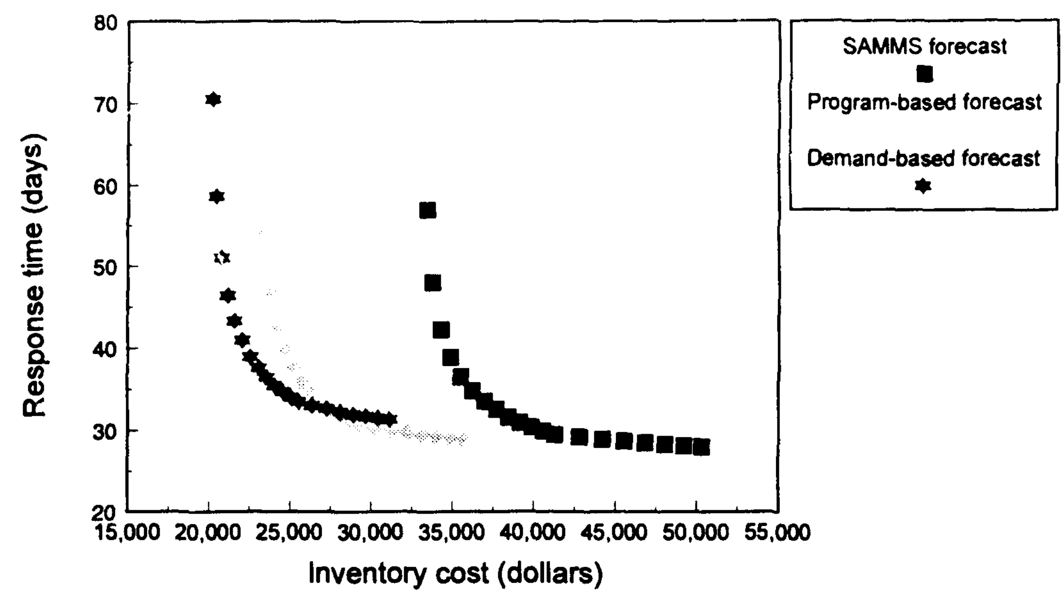

Figure 4-5.
Response Time as a Function of Inventory Investment for Items on Up-and-Down Density Systems

In these runs the exponential smoothing constants were equal to .2. The correcting smoothing constant in the SAMMS algorithm was .35. We used these values, since they had been the DLA default values for some time, although some DLA centers have recently reduced the value of the smoothing constants. We will say more about smoothing constants later. In Figure 4-2 the program-based and demand based methods, as expected, yielded virtually identical results, since program has no effect when stable.

Our criterion for preferring one method to another is that the first achieves the same response time at less inventory cost than the second. Thus, if the curves never crossed one another, there would be a clearly preferred method. Sometimes, however, the curves do cross, indicating that one method is preferred for some response time range while another is preferred for a different response time range. One way of overcoming this dilemma is to decide which response time range is more representative of actual operating conditions. In our case, the crossing points occur on the flat part of the curves, where there is little improvement in response time per additional dollar in inventory cost. We believe that these are uneconomical regions of operation. Therefore, we judged the forecast methods on how they compared on response times greater than those at any of the crossing points.

With this in mind, our conclusion is that exponential smoothing of demand is preferable to a density-based forecast. Only on the group of decreasing densities is the density-based method preferred, and even here, it outperforms the demand-based method by only a small margin.

Figure 4-3, showing the curves for increasing-density systems, displays an odd pattern in which the curves are virtually separate from one another. We found that this seeming anomaly was due to the Navy F/A-18, in which an unusual number of expensive items dominated the cost but had no safety level because of their high price. Figure 4-6 shows the results for the increasing-density group with the F/A-18 items removed; the curves appear more like those for the other groups. Figure 4-7, which is for all groups with the F/A-18 items removed, indicates that exponential smoothing of demand is still preferred overall even without the undue effect of the F/A-18 items.

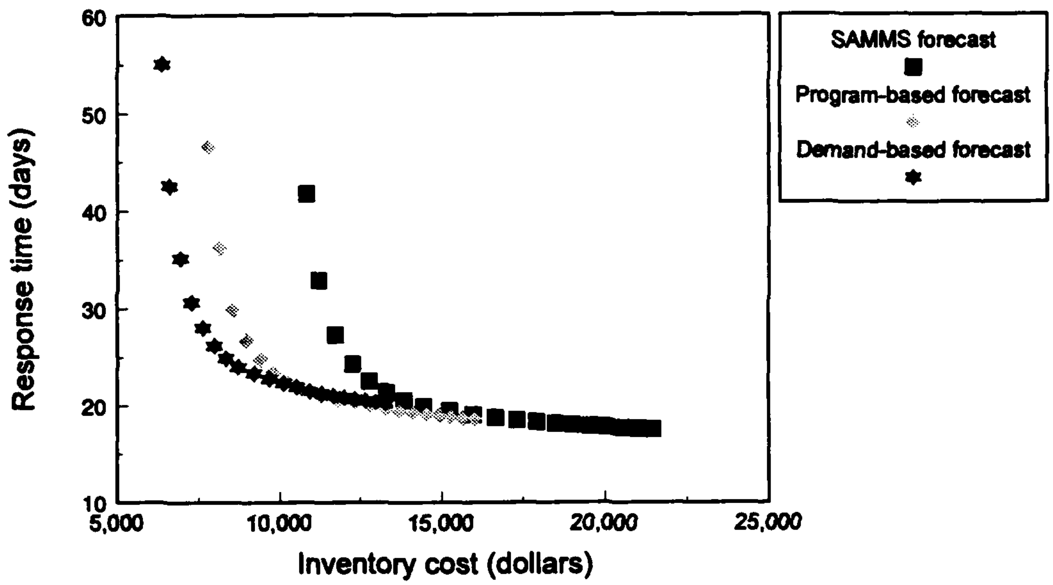

Figure 4-6.
Response Time as a Function of Inventory Investment for Items on Increasing-Density Systems; F/A-18 Items Removed

We also evaluated some combination forecasts for the decreasing-density items to see if we could get further improvement by tempering the impact of program on the forecast. We could not. Figure 4-8 shows one result when program was given a weight of .25 and demand a weight of .75. These combination runs produced curves falling between exponential smoothing of demand and program-based forecasts.

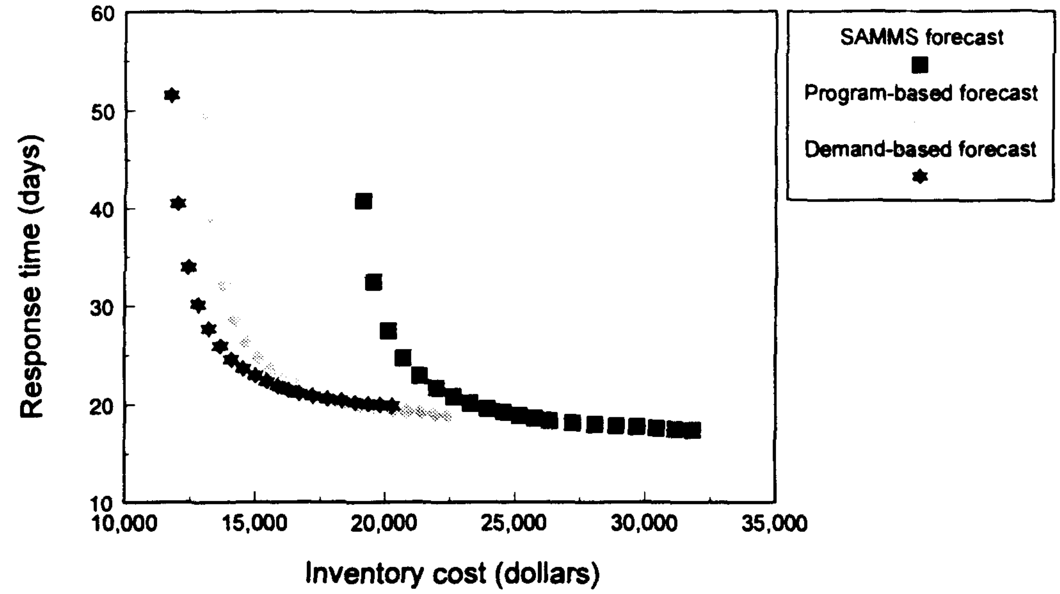

Figure 4-7.
Response Time as a Function of Inventory Investment for All Items with Density Data Except Those on F/A-18

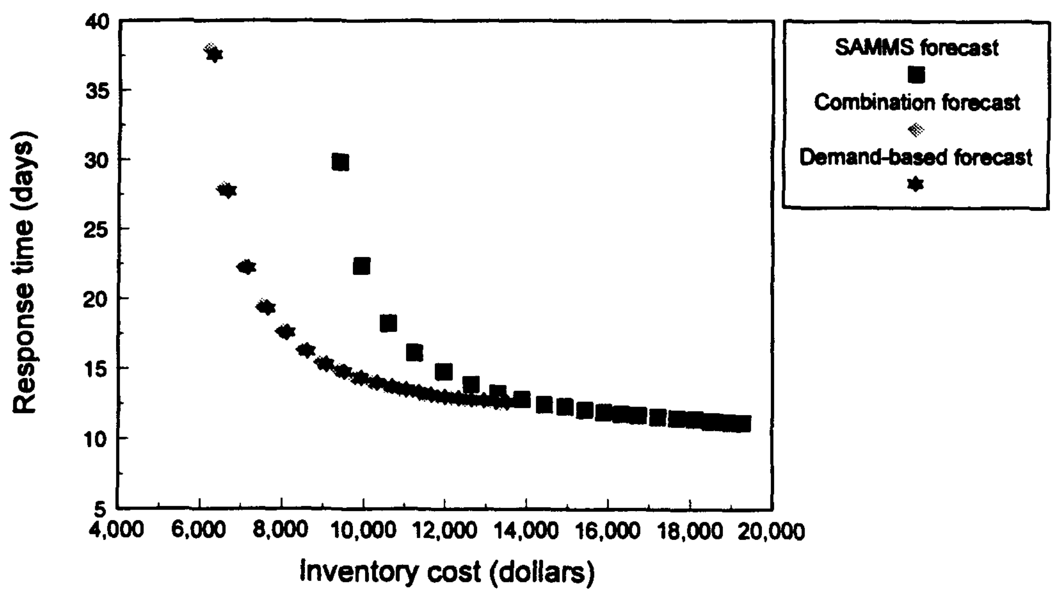

Figure 4-8.
Response Time as a Function of Inventory Investment for Items on Decreasing-Density Systems; Combination Forecast

Finally, we looked briefly at the effect of changing the smoothing constant. Because of the extreme variability in demand, we suspected that smaller values for the smoothing constant would be preferable. We tried a smoothing constant of .1 and a SAMMS correcting constant of .2. For the sake of comparison, a smoothing constant of .2 is said to correspond to a 9-quarter moving average, while a constant of .1 corresponds to a 19-quarter moving average[2]. The results in Figure 4-9 indicate a significant improvement in all three methods using the smaller constant.

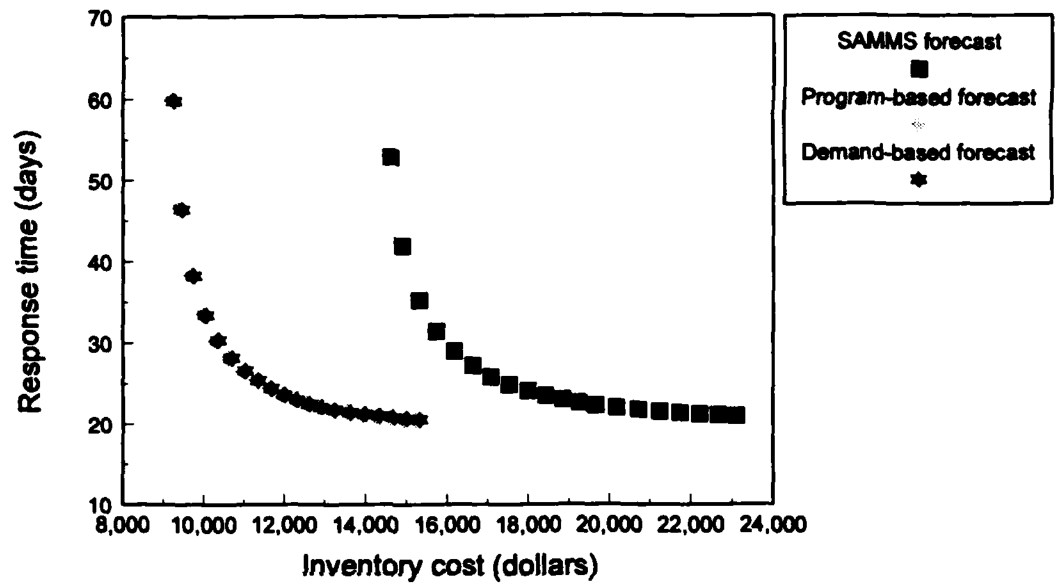

Figure 4-9.
Response Time as a Function of Inventory Investment for All Items with Density Data; Smoothing Constant = .1

FLYING HOUR FINDINGS

Table 4-2 shows the number of weapon systems in each flying hour pattern group, along with the associated number of parts simulated. The B-2 bomber was not included, because it was not introduced until late in our demand history.

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[2] R.A. Brown suggested comparing exponential smoothing with a moving average on the basis of the average age of the data used to make the forecast. For an exponential smoothed forecast with the same age of data as an N-quarter moving average, set the smoothing constant = 2/N + 1.

Table 4-2.
Weapon-System Flying Hour Groups

Group type	Number of systems	Number of parts simulated
Stable	11	4,563
Increasing	6	1,977
Decreasing	10	2,231
Up and down	1	160
Total	28	8,931

Figures 4-10 through 4-14 are the response-time versus inventory cost curves for the total and various flying hour pattern groups. The flying hour results are similar to those for density. Single exponential smoothing of demand is preferred overall, while program-based forecasting does best only on the decreasing-flying-hour group. Again, in this case, the program-based method is only marginally better than single exponential smoothing of demand.

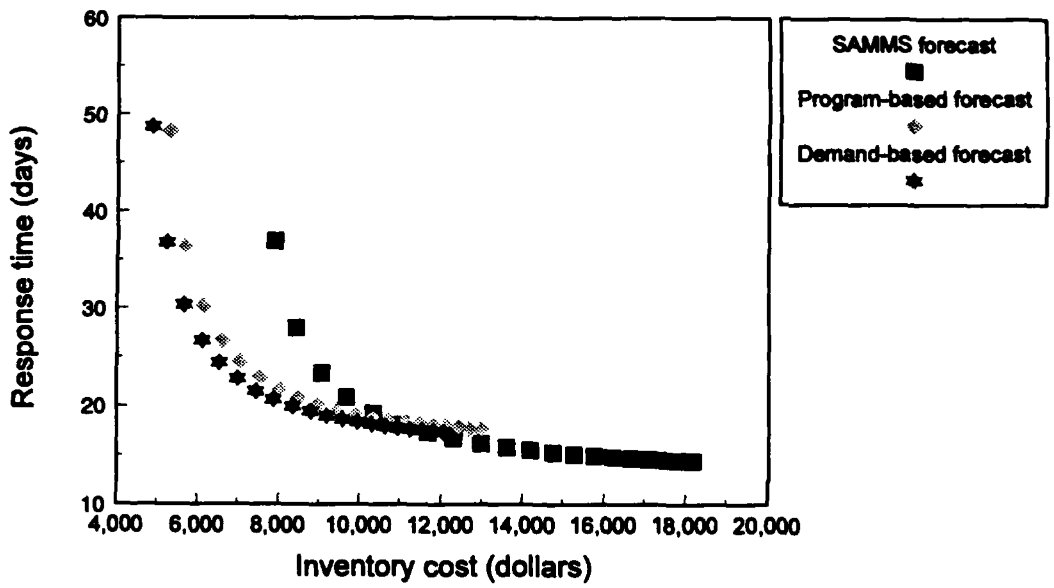

Figure 4-10.
Response Time as a Function of Inventory Investment for All Items on Systems with Flying Hour Data

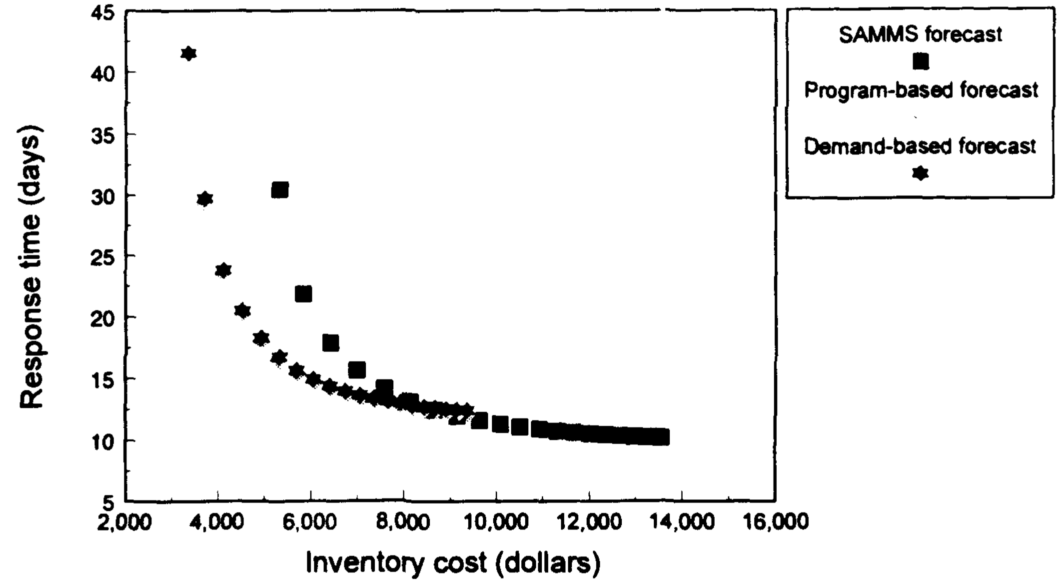

Figure 4-11.
Response Time as a Function of Inventory Investment for Items on Stable-Flying-Hour Systems

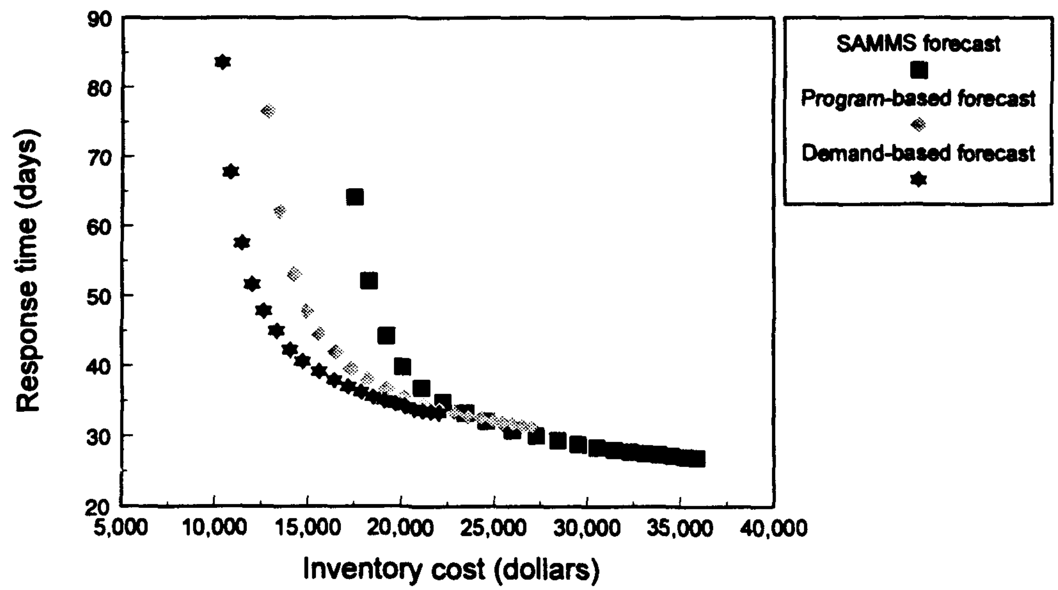

Figure 4-12.
Response Time as a Function of Inventory Investment for Items on Increasing-Flying-Hour Systems

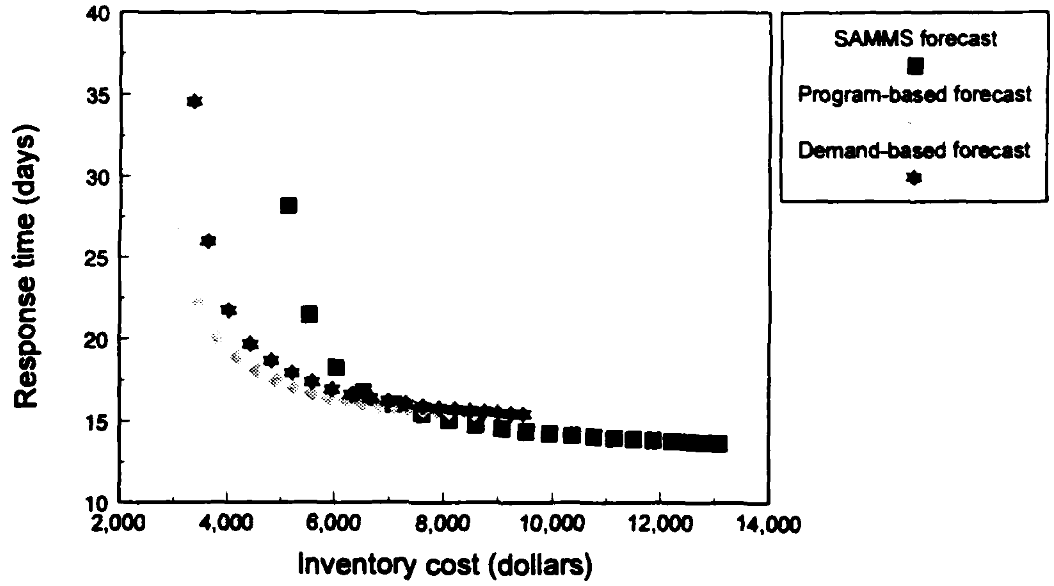

Figure 4-13.
Response Time as a Function of Inventory Investment for Items on Decreasing-Flying-Hour Systems

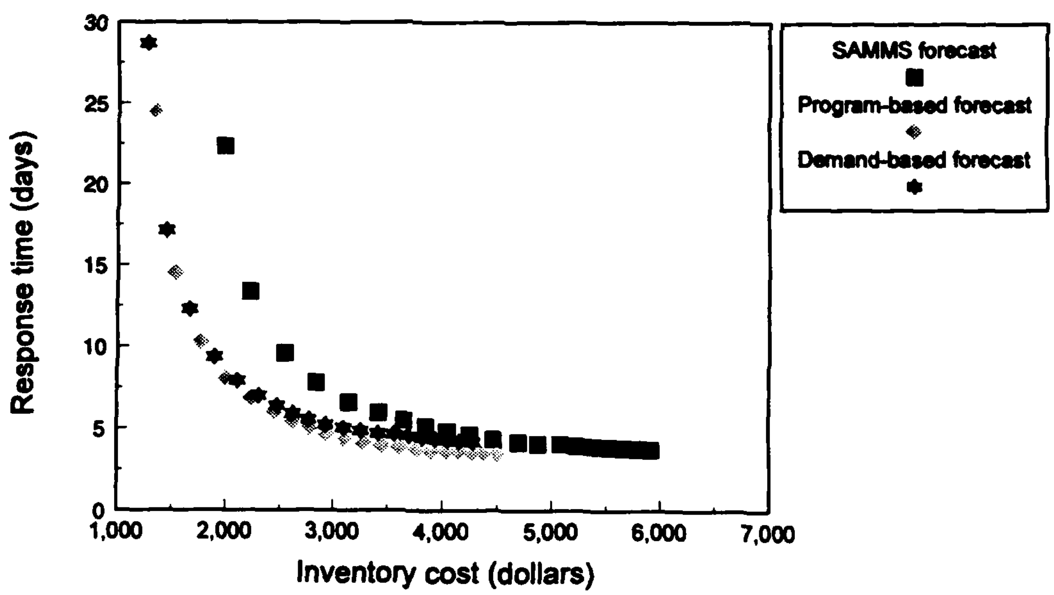

Figure 4-14.
Response Time as a Function of Inventory Investment for Items on Up-and-Down Flying Hour Systems

Figure 4-15 shows the curves when the smoothing constant is reduced to .1. Again, as with density, there is a significant improvement in all methods when the smoothing constant is reduced.

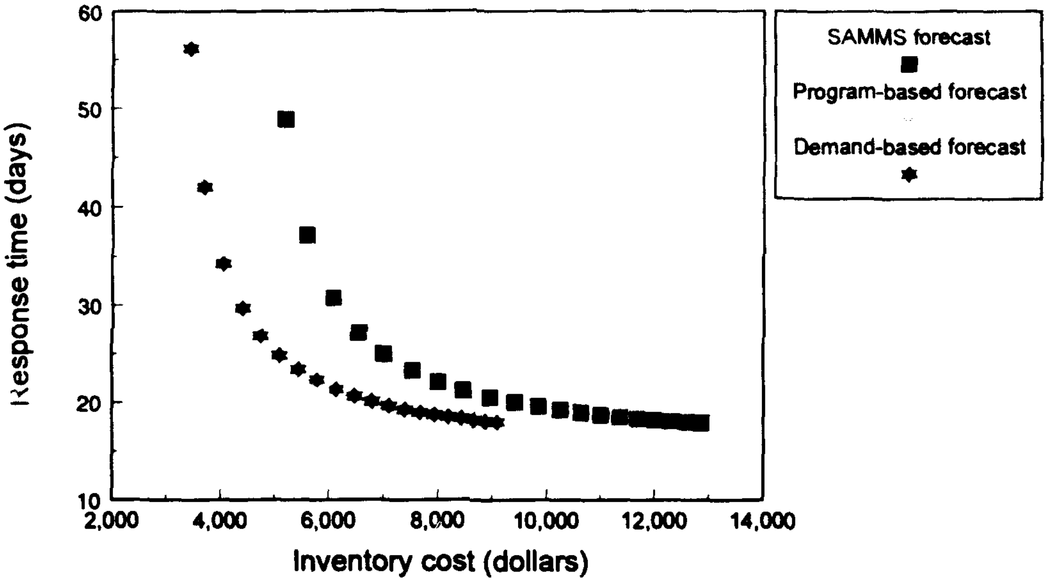

Figure 4-15.
Response Time as a Function of Inventory Investment for Items on All Weapon Systems with Flying Hour Data; Smoothing Constant = .1

Implementation Issues

Since program-based forecasting did offer a slight performance edge for weapon systems with decreasing densities, it is natural to ask whether it would be worth implementing program-based forecasts for those systems.

If are asking about systemic implementation of program-based forecasts for items on weapon systems with decreasing density, the answer is "no," for the following reasons:

- Program-based forecasts require an extensive effort to collect program data, as we discovered in preparing for this study.
- Planned programs for some weapon systems may be classified. DLA is not currently authorized to handle classified data.

- For multiple-application items, it is difficult, if not impossible, to attribute demands to specific weapons systems. For example, if a bolt is used on both a tank and a truck, how is DLA to know how many of the bolts ordered by the Army are for tanks, and how many are for trucks? To our knowledge, no one currently collects this information, and for many items it is difficult to see how it *could* be collected.

However, program-based forecasts for *single-application items* on a *limited number of weapon systems* may be feasible.

In contrast to the program-based forecast, single exponential smoothing of historical demand does not suffer from any of these implementation problems; it can be implemented using data currently available to DLA.

SUMMARY

For programs with a decreasing trend, it is true that program-based forecasting slightly outperforms historical-demand-based forecasting. Overall, however, single exponential smoothing of historical demand is superior to program-based forecasting, regardless of whether the program is weapon system density or planned flying hours. As discussed above, single exponential smoothing of demand also avoids the extensive data collection effort required by a program-based method.

We also observed that using a smaller smoothing constant than the one traditionally used by DLA improves the results obtained by all forecast methods and leads to less of a difference between the program-based and demand-based results. The SAMMS algorithm was consistently the poorest of the three forecasting methods evaluated because, we believe, it is the one most sensitive to recent demand.

CHAPTER 5

Conclusions and Recommendations

The correlation between weapon system programs and single application item demand is weak to moderate for most of the 94 weapon systems we considered. This finding is consistent with our observation that the sharp peaks and troughs in a weapon system's demand pattern overwhelm any trend component paralleling the weapon system program.

For the few weapon systems that exhibited a strong correlation, we found no defining characteristic; they included systems as diverse as the Navy's *Ticonderoga*-class cruiser, the Army's HMMWV ("Hum-Vee"), and the Air Force's F-16 Fighting Falcon.

When we evaluated program-based and demand-based forecast methods in an inventory simulator, we found that single exponential smoothing, a demand-based forecast, outperformed the program-based forecast, except on weapon systems with decreasing program, and there the difference was small. Both alternatives consistently outperformed the current SAMMS method, which is especially sensitive to recent demand. Considering feasibility, the program-based forecast is too difficult to implement systematically: it requires extensive effort to collect program data, the program data may be classified, and attributing demands to specific weapon systems is difficult or impossible for multiple-application items. It may be feasible for single-application items on a small number of weapon systems. None of these difficulties affect single exponential smoothing of historical demand.

We recommend that DLA replace the current SAMMS method with single exponential smoothing of historical demand, when DLA's new Composite Forecasting becomes available. (Single exponential smoothing of historical demand is an option under Composite Forecasting.)

Since our results show some advantage in program-based forecasting when a weapon system's program is decreasing, yet do not support an overall use of program-based forecasting, we recommend that DLA arrange to obtain information from the Services on systems that are being phased out. Item manager knowledge could be used effectively in these cases to reduce buy quantities for stock levels, especially on items that used on only a few systems.

To an extent, the differences between the results obtained from the two alternatives were due to the size of the smoothing constant; when we decreased that constant from 0.2 to 0.1, the differences in performance narrowed greatly. Traditionally, DLA has used a smoothing constant of 0.2 that corresponds (in terms of "data age") to a nine-quarter moving average. DLA should consider using a

longer base period (smaller smoothing constant) when implementing Composite Forecasting.

Finally, we found that the DLA weapon system data base is not entirely adequate for identifying item applications. For example, it identified items appearing in the Army demand history as belonging to weapon systems such as a battleships and submarines. We recommend that DLA improve the application data base before implementing Multi-Link or any other inventory management system that depends upon weapon system application data.

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APPENDIX A

Correlation Results for Densities and Nonoverhaul Demand

Correlation Results for Densities and Nonoverhaul Demand

Table A-1.
Correlation of Nonoverhaul Demand with Densities

Weapon system	WSDC	Maximum correlation
LGM-30 Minuteman missile	01F	not significant
UH-1 Iroquois helicopter	02A	not significant
F-4 Phantom aircraft	02F	0.45
Benjamin Franklin-class submarine	03N	not significant
B-52 Stratofortress aircraft	04F	not significant
C-135 Stratolifter aircraft	05F	negative
C-130 Hercules aircraft (non-SOF)	06F	0.55
M-551 Sheridan tank	07A	not significant
F-106 Delta Dart aircraft	09F	0.81
F-111 aircraft	10F	not significant
F-14 Tomcat aircraft	10N	0.6
C-5 Galaxy aircraft	11F	0.45
TOW	12A	not significant
C-141 Starlifter aircraft	12F	not significant
H-3 Green Giant helicopter	15F	not significant
H-53 Super Jolly helicopter	16F	0.5
S-3A Viking aircraft	16N	0.35
A-7D Corsair aircraft	17F	0.35
E-2C Hawkeye aircraft	17N	not significant
A-6E aircraft	18N	0.6
KA-6D Intruder aircraft	19N	not significant
F-15 Eagle aircraft	19F	0.4
F-5 Freedom fighter	21F	0.4
HH-1 Iroquois helicopter	22F	0.65
M-109 howitzer	23A	not significant
Ohio-class submarine	23N	0.35
A-10 Thunderbolt II aircraft	24F	not significant
M-102 howitzer	25A	not significant

Note: WSDC = weapon system designator code; SOF = Special Operations Forces; TOW = tube launched, optically tracked, wire-guided missile; and AWACS = airborne warning and control system.

Table A-1.
Correlation of Nonoverhaul Demand with Densities (Continued)

Weapon system	WSDC	Maximum correlation
E-3A AWACS aircraft	25F	not significant
M-29 mortar	26A	not significant
F-16 Fighting Falcon aircraft	26F	0.8
M-60 tank	30A	0.45
OH-58 Kiowa helicopter	32A	not significant
Cobra Helicopter, AH series	34A	not significant
M-198 155mm howitzer	35A	not significant
M-1 Abrams tank	36A	not significant
Bradley Fighting Vehicle	37A	0.5
Stinger missile	38A	not significant
H-2 Seasprite helicopter	38N	not significant
Patriot missile	39A	0.45
H-3 Sea King helicopter	39N	not significant
UH-60A Black Hawk helicopter	40A	0.5
H-46 Sea Knight helicopter	40N	not significant
T-37 aircraft	41F	negative
T-38 aircraft	42F	0.5
F/A-18 Hornet aircraft	43N	0.65
OV-1D Mohawk aircraft	44A	negative
SH-60B LAMPS MARK III helicopter	44N	0.6
EA-6B Prowler aircraft	45N	not significant
AH-1J Cobra helicopter	47N	not significant
UH-1N search and recovery helicopter	48N	0.35
A-4 Skyhawk aircraft	52N	not significant
EA-6A aircraft	53N	not significant
B-1B aircraft	56F	not significant
KC-130 Hercules aircraft	59N	not significant
AH-64 Apache helicopter	61A	0.75
Multiple Launch Rocket System (MLRS)	62A	0.6
OV-10 Bronco aircraft	62N	0.4
P-3 Orion aircraft	63N	not significant
M101-A1 Light, Towed 105mm howitzer	6DM	not significant
M-114-A2 Medium, Towed 155mm howitzer	6EM	0.5
M-110-A2 heavy 8 inch howitzer	6GM	0.4

Note: WSDC = weapon system designator code; SOF = Special Operations Forces; TOW = tube-launched, optically tracked, wire-guided missile; and AWACS = airborne warning and control system.

Table A-1.
Correlation of Nonoverhaul Demand with Densities (Continued)

Weapon system	WSDC	Maximum correlation
M-109 A1, A3 155mm howitzer	6JM	not significant
M29-A1 81mm mortar	6KM	not significant
M-915 Series, M-916A1 truck	73A	negative
M-939 5-ton truck	79A	0.75
Vehicle System, 1-1/4 ton (HMMWV)	80A	0.75
Special Operations C-130 aircraft	ATF	not significant
T-39 aircraft	CDF	0.5
M-114 A-2 medium, towed 155mm howitzer	EAA	not significant
M-203 40mm Grenade Launcher	EBA	not significant
M-2 0.50 caliber machine gun	ECA	not significant
M-85 0.50 caliber machine gun	EDA	not significant
M-60 7.62mm Machine Gun	EGA	not significant
E-4B airborne command post	EJF	not significant
Los Angeles-class submarine	EXN	not significant
Strurgeon-class submarine	EYN	not significant
Ticonderoga-class cruiser	EZN	0.65
Virginia-class cruiser	FAN	not significant
Spruance-class destroyer	FBN	not significant
Forrestal-class aircraft carrier	HZN	0.6
Nimitz-class aircraft carrier	JAN	not significant
Iowa-class battleship	JBN	not significant
Kidd-class destroyer	JCN	not significant
Belknap-class cruiser	JEN	not significant
Oliver Perry-class guided missile frigate	JFN	not significant
Tarawa-class amphibious assault ship	JLN	not significant
Knox-class Frigate	JRN	0.6
Whidbey Island-class dock landing ship	JSN	0.75
Newport-class tank landing ship	JWN	not significant
Iwo Jima-class amphibious assault helicopter carrier	JYN	not significant
Blue Ridge-class amphibious warfare ship	MQN	not significant
M-231 Port Firing 5.5mm machine gun	PMA	not significant
M-1 A-1 tank	UKM	0.6

Note: WSDC = weapon system designator code; SOF = Special Operations Forces; TOW = tube-launched, optically tracked, wire-guided missile; and AWACS = airborne warning and control system.

Appendix B

Correlation Results for Densities and Total Demand

Correlation Results for Densities and Total Demand

Table B-1.
Correlation of Total Demand with Densities

Weapon system	WSDC	Maximum correlation
LGM-30 Minuteman missile	01F	not significant
UH-1 Iroquois helicopter	02A	not significant
F-4 Phantom aircraft	02F	0.6
Benjamin Franklin-class submarine	03N	not significant
B-52 Stratofortress aircraft	04F	not significant
C-135 Stratolifter aircraft	05F	negative
C-130 Hercules aircraft (non-SOF)	06F	0.45
M-551 Sheridan tank	07A	not significant
F-106 Delta Dart aircraft	09F	0.8
F-111 aircraft	10F	not significant
F-14 Tomcat aircraft	10N	0.45
C-5 Galaxy aircraft	11F	0.7
TOW	12A	not significant
C-141 Starlifter aircraft	12F	negative
H-3 Green Giant helicopter	15F	not significant
H-53 Super Jolly helicopter	16F	0.5
S-3A Viking Aircraft	16N	0.5
A-7D Corsair aircraft	17F	0.5
E-2C Hawkeye aircraft	17N	not significant
A-6E aircraft	18N	0.6
KA-6D Intruder aircraft	19N	not significant
F-15 Eagle aircraft	19F	0.75
F-5 Freedom fighter	21F	0.3
HH-1 Iroquois helicopter	22F	0.6
M-109 howitzer	23A	not significant
Ohio-class submarine	23N	not significant
A-10 Thunderbolt II aircraft	24F	not significant
M-102 howitzer	25A	not significant

Table B-1.
Correlation of Total Demand with Densities (Continued)

Weapon system	WSDC	Maximum correlation
E-3A AWACS aircraft	25F	not significant
M-29 mortar	26A	not significant
F-16 Fighting Falcon aircraft	26F	0.9
M-60 Tank	30A	0.5
OH-58 Kiowa helicopter	32A	not significant
Cobra helicopter, AH series	34A	not significant
M-198 155mm howitzer	35A	not significant
M-1 Abrams tank	36A	not significant
Bradley Fighting Vehicle	37A	0.45
Stinger missile	38A	not significant
H-2 Seasprite helicopter	38N	not significant
Patriot missile	39A	0.5
H-3 Sea King helicopter	39N	not significant
UH-60A Black Hawk helicopter	40A	0.45
H-46 Sea Knight helicopter	40N	not significant
T-37 aircraft	41F	negative
T-38 aircraft	42F	0.4
F/A-18 Hornet aircraft	43N	0.75
OV-1D Mohawk aircraft	44A	negative
SH-60B LAMPS MARK III helicopter	44N	0.65
EA-6B Prowler aircraft	45N	not significant
AH-1J Cobra helicopter	47N	0.4
UH-1N search and recovery helicopter	48N	0.4
A-4 Skyhawk aircraft	52N	0.35
EA-6A aircraft	53N	not significant
B-1B aircraft	56F	0.8
KC-130 Hercules aircraft	59N	not significant
AH-64 Apache helicopter	61A	0.7
Multiple Launch Rocket System (MLRS)	62A	0.6
OV-10 Bronco aircraft	62N	not significant
P-3 Orion aircraft	63N	0.35
M101-A1 light, towed 105mm howitzer	6DM	not significant
M-114-A2 medium, towed 155mm howitzer	6EM	0.5
M-110-A2 heavy 8 inch howitzer	6GM	0.4

Table B-1.
Correlation of Total Demand with Densities (Continued)

Weapon system	WSDC	Maximum correlation
M-109 A1, A3 155mm howitzer	6JM	negative
M29-A1 81mm mortar	6KM	not significant
M-915 series, M-916A1 truck	73A	negative
M-939 5-ton truck	79A	0.65
Vehicle system, 1-1/4 ton (HMMWV)	80A	0.75
Special operations C-130 aircraft	ATF	not significant
T-39 aircraft	CDF	not significant
M-114 A-2 medium, towed 155mm howitzer	EAA	not significant
M-203 40mm grenade launcher	EBA	not significant
M-2 0.50 caliber machine gun	ECA	not significant
M-85 0.50 caliber machine gun	EDA	not significant
M-60 7.62mm machine gun	EGA	not significant
E-4B Airborne command post	EJF	not significant
Los Angeles-class submarine	EXN	not significant
Strurgeon-class submarine	EYN	not significant
Ticonderoga-class cruiser	EZN	0.65
Virginia-class cruiser	FAN	not significant
Spruance-class destroyer	FBN	not significant
Forrestal-class aircraft carrier	HZN	0.6
Nimitz-class aircraft carrier	JAN	not significant
Iowa-class battleship	JBN	not significant
Kidd-class destroyer	JCN	not significant
Belknap-class cruiser	JEN	not significant
Oliver Perry-class guided missile frigate	JFN	not significant
Tarawa-class amphibious assault ship	JLN	not significant
Knox-class frigate	JRN	0.6
Whidbey Island-class dock landing ship	JSN	0.5
Newport-class tank landing ship	JWN	not significant
Iwo Jima-class Amphibious assault helicopter carrier	JYN	not significant
Blue Ridge-class Amphibious warfare ship	MQN	not significant
M-231 Port Firing 5.5mm machine gun	PMA	not significant
M-1 A-1 tank	UKM	0.6

Appendix C

Correlation Results for Nonoverhaul Demand and Flying Hours

Correlation Results for Nonoverhaul Demand and Flying Hours

Table C-1.
Correlation of Nonoverhaul Demand with Flying Hours

Weapon system	WSDC	Maximum correlation
UH-1 Iroquois helicopter	02A	not significant
F-4 Phantom Aircraft (Air Force version)	02F	0.45
B-52 Stratofortress aircraft	04F	not significant
CH-47 Chinook helicopter	05A	negative
C-135 Stratolifter aircraft	05F	not significant
C-130 Hercules (non-SOF)	06F	0.4
F-111 aircraft	10F	0.4
F-14 Tomcat aircraft	10N	not significant
C-5 Galaxy aircraft	11F	not significant
C-141 Starlifter aircraft	12F	negative
H-3 Green Giant helicopter	15F	not significant
H-53 Super Jolly helicopter	16F	negative
S-3A Viking aircraft	16N	0.5
A-7D Corsair	17F	0.45
E-2C Hawkeye	17N	not significant
A-6E aircraft	18N	not significant
F-15 Eagle aircraft	19F	0.4
KA-6D Intruder	19N	not significant
E-6 Tacamo	20N	0.5
F-5 Freedom Fighter	21F	0.55
HH-1 Iroquois helicopter	22F	not significant
A-10 Thunderbolt II aircraft	24F	not significant
E-3A AWACS aircraft	25F	not significant
F-16 Fighting Falcon aircraft	26F	0.8
OH-58 Kiowa helicopter	32A	0.45
Cobra Helicopter, AH series	34A	0.35
H-2 Seasprite helicopter	38N	not significant
H-3 Sea King helicopter	39N	0.7

Table C-1.
Correlation of Nonoverhaul Demand with Flying Hours (Continued)

Weapon system	WSDC	Maximum correlation
UH-60 Black Hawk helicopter	40A	0.45
H-46 Sea Knight helicopter	40N	not significant
T-37 aircraft	41F	negative
T-38 aircraft	42[illegible]	0.3
F/A-18 Hornet aircraft	43N	0.5
SH-60B LAMPS MARK III helicopter	44N	not significant
EA-6B Prowler aircraft	45N	not significant
AH-1J Cobra Attack helicopter	47N	0.5
UH-1N search and recovery helicopter	48N	0.5
A-4 Skyhawk aircraft	52N	0.8
EA-6A aircraft	53N	not significant
AV-8B Harrier aircraft	55N	0.6
B-1B aircraft	56F	0.8
KC-130 Hercules aircraft	59N	not significant
AH-64 Apache helicopter	61A	0.7
F-4 Phantom (Navy version)	61N	0.5
P-3 Orion aircraft	63N	0.5
Pave Hawk HH-MH60G helicopter	75F	0.7
Special operations C-130	ATF	not significant
SH-60F anti-submarine warfare helicopter	ERN	not significant
B-2 aircraft	FMF	0.5
T-1A aircraft	MZF	not significant

Appendix D

Correlation Results for Total Demand and Flying Hours

Correlation Results for Total Demand and Flying Hours

Table D-1.
Correlation of Total Demand with Flying Hours

Weapon system	WSDC	Maximum correlation
UH-1 Iroquois helicopter	02A	not significant
F-4 Phantom aircraft (Air Force version)	02F	0.6
B-52 Stratofortress aircraft	04F	not significant
CH-47 Chinook helicopter	05A	negative
C-135 Stratolifter aircraft	05F	not significant
C-130 Hercules (non-SOF)	06F	0.4
F-111 aircraft	10F	0.45
F-14 Tomcat aircraft	10N	0.5
C-5 Galaxy aircraft	11F	0.35
C-141 Starlifter aircraft	12F	negative
H-3 Green Giant helicopter	15F	not significant
H-53 Super Jolly helicopter	16F	negative
S-3A Viking aircraft	16N	0.7
A-7D Corsair	17F	0.55
E-2C Hawkeye	17N	not significant
A-6E aircraft	18N	negative
F-15 Eagle aircraft	19F	0.7
KA-6D Intruder	19N	not significant
E-6 Tacamo	20N	not significant
F-5 Freedom Fighter	21F	0.45
HH-1 Iroquois helicopter	22F	not significant
A-10 Thunderbolt II aircraft	24F	not significant
E-3A AWACS aircraft	25F	not significant
F-16 Fighting Falcon aircraft	26F	0.9
OH-58 Kiowa helicopter	32A	0.45
Cobra Helicopter, AH series	34A	0.35
H-2 Seasprite helicopter	38N	not significant
H-3 Sea King helicopter	39N	0.6

Table D-1.
Correlation of Total Demand with Flying Hours (Continued)

Weapon system	WSDC	Maximum correlation
UH-60 Black Hawk helicopter	40A	0.5
H-46 Sea Knight helicopter	40N	0.5
T-37 aircraft	41F	negative
T-38 aircraft	42F	not significant
F/A-18 Hornet aircraft	43N	0.6
SH-60B LAMPS MARK III helicopter	44N	not significant
EA-6B Prowler aircraft	45N	not significant
AH-1J Cobra Attack helicopter	47N	0.5
UH-1N search and recovery helicopter	48N	not significant
A-4 Skyhawk aircraft	52N	0.8
EA-6A aircraft	53N	not significant
AV-8B Harrier aircraft	55N	0.6
B-1B aircraft	56F	0.8
KC-130 Hercules aircraft	59N	not significant
AH-64 Apache helicopter	61A	0.7
F-4 Phantom (Navy version)	61N	0.5
P-3 Orion aircraft	63N	0.55
Pave Hawk HH-MH60G helicopter	75F	0.7
Special operations C-130	ATF	not significant
SH-60F anti-submarine warfare helicopter	ERN	not significant
B-2 aircraft	FMF	not significant
T-1A aircraft	MZF	not significant

APPENDIX E

Correlation Results for Overhaul Demand and Programmed Overhauls

Correlation Results for Overhaul Demand and Programmed Overhauls

Table E-1.
Correlation of Overhaul Demands with Programmed Overhauls

Weapon system	WSDC	Maximum correlation
F-4 Phantom aircraft	02F	0.7
B-52 Stratofortress aircraft	04F	not significant
C-135 Stratolifter aircraft	05F	not significant
C-130 Hercules aircraft (non-SOF)	06F	not significant
F-106 Delta Dart aircraft	09F	0.5
F-111 aircraft	10F	not significant
C-5 Galaxy aircraft	11F	0.5
C-141 Starlifter aircraft	12F	not significant
H-3 Green Giant helicopter	15F	0.5
H-53 Super Jolly helicopter	16F	not significant
A-7D Corsair aircraft	17F	not significant
F-15 Eagle aircraft	19F	not significant
F-5 Freedom Fighter	21F	not significant
HH-1 Iroquois helicopter	22F	not significant
A-10 Thunderbolt II aircraft	24F	not significant
E-3A AWACS aircraft	25F	not significant
F-16 Fighting Falcon aircraft	26F	0.5
T-37 aircraft	41F	not significant
T-38 aircraft	42F	not significant
OV-10 aircraft	53F	not significant
B-1B aircraft	56F	not significant
Pave Hawk HH/MH-60G helicopter	75F	0.5
Special operations C-130 aircraft	ATF	not significant
T-39 aircraft	CDF	not significant

Appendix F

Glossary

Glossary

AF/XOOT	=	Office of the Deputy Chief of Staff for Plans and Operations (Air Force)
AWACS	=	airborne warning and control system
DCSOPs	=	Deputy Chief of Staff for Operations and Plans (Army)
DIDB	=	DLA Integrated Data Bank
DLA	=	Defense Logistics Agency
DoDAAC	=	DoD Activity Address Code
DORO	=	DLA's Operations Research Office
FMS	=	Foreign Military Sales
FY	=	fiscal year
JLSC	=	Joint Logistics Systems Center
LMI	=	Logistics Management Institute
MAP	=	military assistance program
MD	=	mission design
MDS	=	mission design series
NSN	=	national stock number
OSD, PA&E	=	Office of the Secretary of Defense, Program Analysis and Evaluation
SAMMS	=	Standard Automated Materiel Management System
SOF	=	Special Operations Forces
TMSs	=	type mission series
TS	=	Tracking Signal
WSDC	=	weapon system designator code
WSSP	=	Weapon System Support Program